Norwegian University of Life Sciences
School of Economics and Business (HH)

Philosophiae Doctor (PhD)
Thesis 2021:66

# Essays on the Reformed Norwegian Electricity Retail Market

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Kari-Anne Fange

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Ås 2021

Thesis number 2021:66

ISSN 1894-6402

ISBN 978-82-575-1737-3

# Acknowledgments

I definitely have many people to thank for making this project possible.

I would first like to thank Østfold University College (HIØ) for providing financial funding, and the Norwegian University of Life Sciences and the School of Economics and Business (HH) for enrolling me in their PhD program. Next, I would like to thank my supervisor, Associate Professor Olvar Bergland, for introducing me to the exciting field of Industrial Organization and electricity markets and for insightful discussions that pushed me to sharpen my thinking about the topic. I would also like to thank my co-supervisor, Associate Professor Bjørnar Karlsen Kivedal, for valuable and encouraging discussions over many years as colleagues at HIØ.

My thanks also go to Associate Professor Kristine Grimsrud for being my mentor and friend during my year in graduate school at UNM in Albuquerque, NM. In addition, I would like to express my gratitude to the former Head of Studies of faculty of Business, Languages, and Social Sciences at HIØ, Theo Schewe. Thank you for motivating me to keep up the work, and for being my friend. Thanks are also due to Professor Mette Bjørndal and Professor Endre Bjørndal at NHH for introducing me to the topic of electricity network regulation and for sharing your in-depth knowledge.

To Elise: One of my definitely lucky shots was ending up in a shared office space with you at HIØ. I am proud to call you my close friend. Thank you for being my great inspiration and support in academic as well as everyday life matters.

Finally and wholeheartedly, I would like to thank Henrik for having faith in me. You are the most generous person I know. Your support and generosity have undoubtedly made this project possible. And to my children Agnes, Olaf and Gustav: thank you for being my source of inspiration and for giving me the most valuable perspective, every day.

August 2021

Kari-Anne Fange

# Contents

# List of papers

1. Benchmarking in Regulation of Electricity Networks in Norway -An Overview
   (Endre Bjørndal, Mette Bjørndal og Kari-Anne Fange)
   *In Energy, Natural Resources and Environmental Economics*

2. Household Choice of Electricity Retailer
   (Kari-Anne Fange)

3. Electricity Retailing and Price Dispersion
   (Kari-Anne Fange)

4. Price Leadership and Electricity Retailing
   (Kari-Anne Fange and Olvar Bergland)

# Summary

The thesis explores efficiency outcomes following the Norwegian electricity market reform introduced in the early 1990s. Specifically, the thesis investigates efficiency outcomes resulting from the incentive regulation of electricity network companies, the inherent nature of household consumers and their attitudes to market participation, electricity price development in standard electricity contracts, and the potential for facilitating practices to increase collusive market behavior among retailers. The thesis consists of an extensive introductory chapter that comprises the context and background information to the four empirical studies, data, methods and a summary. Using rich data and sophisticated methods, the thesis brings new evidence to bear on the economics and psychology of household switching behavior of electricity retailers, development in electricity contract prices, and market behavior among retailers.

The first paper provides an overview of the benchmarking models used in Norwegian incentive regulation from 1997-2011. The paper also addresses concerns related to model specification, and examines the choice of scale assumptions and input/output variables and their use in benchmarking models. The results show that thorough knowledge of the cost structures and cost drivers of the industry is of great importance in specifying models and data measurement choices. Such choices may have a substantial effect on efficiency scores and thus revenue caps. The paper argues that in order to achieve the goals of incentive regulation, some adjustments to the benchmarking results may be necessary.

The second paper explores the factors that determine a household's decision to switch electricity retailer, applying a theoretical framework that embraces both economic and psychological influences to explain consumers' switch decisions. Using a detailed survey dataset on household preferences in electricity-related issues and a probit model framework, the study shows that both issues related to market design and psychological factors seem important in inducing households' switch choices. In addition, the paper sheds light on concerns related to sample selection and potential self-selecting bias in Internet panels.

The third paper studies price dispersion in electricity contracts from the perspective

that prices for homogeneous goods should converge according to the "law of one price". First, informal descriptive observations of the data indicate that prices do not converge. Next, the paper uses a cointegrated vector error correction model to handle the non-stationary nature of the data and estimate the long-run dynamics of the models. Estimation results show that consumer switch volumes and number of firms offering the specific contracts are significantly reflected in the dispersed contract prices. Thus, a positive shift in switching seem to have a negative effect on dispersion in prices. Whereas, an increased number of firms strengthen price dispersion. In addition, the results reveal a significant trend parameter, which may indicate that factors outside the model are likely to explain some of the dispersion in prices.

The final paper hinges on the findings from the third paper to explore market behavior among nationwide retailers. Using a market structure with price information transparency, enabled by information from an official Web page provided by the National Competition Authority, the paper analyzes the existence of any facilitating behavior that resembles price leadership. We use a sophisticated input-output Markov model framework to assign probabilities that price adjustments stem from collusive behavior. Taken together the results indicate a pattern, in which certain retailers take on a price leader/follower position to drive up/down prices, while others are more or less unaffected by both margin size and price adjustments made by other retailers. Generalizing beyond our study, the results suggest that transparency of price information seem to have an effect on retailers opportunity to adopt market behavior that resembles price leadership/following. Specifically, we observe that certain retailers seem to systematically adopt information to control a specific market position.

The thesis provides new insights into market behavior, consumer choice, and price development to evaluate the expansion of the electricity retail market. The findings indicate that there are issues related to market design, transparency in price information, specific factors influencing consumer's decision making, and mechanisms that seem to facilitate collusive pricing behavior that should not be underestimated when designing policy measures and new regulations for further expansion of the sector in the long run.

# Sammendrag

Denne avhandlingen undersøker og evaluerer reformen innen elektrisitetssektoren som ble innført tidlig på 1990-tallet vurdert fra fire perspektiver: insentivregulering av nettselskap, husholdningskunders aktivitet i sluttbrukermarkedet, prisutviklingen i elektrisitetskontrakter, og markedssvikt som følge av markedsoppførsel som ikke er i tråd med sunn konkurranse. Avhandlingen består av fire artikler samt et introduksjonskapittel som presenterer bakgrunn, data, metode, konklusjon og sammendrag. Artiklene legger til grunn et omfattende datagrunnlag, og benytter avanserte økonometriske metoder for å finne mekanismer og deres empiriske spor som skal besvare spørsmålene som undersøkes. Avhandlingen bidrar til ny innsikt både når det gjelder markedsadferd og prisutvikling.

Den første artikkelen gir en oversikt over benchmark-modellene som ble brukt i insentivregulering av nettselskap mellom 1997-2011. Mer spesifikt kartlegger artikkelen elementer ved modellspesifikasjonene som måler nettselskapenes effektivitet. Det vil si valg av skaleringsparametere og input/output-variabler som kan ha stor betydning for målingene. Resultatene viser at det er svært viktig med gjennomgående god kunnskap om kostnadsstrukturer, kostnadsdrivere og industristrispesifikke opplysninger. Slik kunnskap kan ha stor betydning for effektivitetsmålignene til de enkelte nettselskapene. Dermed også stor betydning for inntektsrammene som blir satt for det enkelte selskap.

Den andre artikkelen undersøker variabler som har betydning for husholdningskunders avgjørelse om å bytte strømleverandør. Analysen tar utgangspunkt i et teoretisk rammeverk som inkluderer både økonomiske og psykologiske perspektiver som grunnlag for bytteavgjørelsen. Datagrunnlaget utgjøres av en omfattende spørreundersøkelse som ble gjennomført av Norges vassdrags- og energidirektorat for å få økt innsikt om husholdningers holdninger og kunnskap i energirelaterte spørsmål. Videre brukes en probit-modell for å estimere om det finnes en signifikant sammenheng mellom ulike faktorer og påstander og husholdningskunders bytteavgjørelse. Analysen finner at både elementer knyttet til økonomiske og psykologiske faktorer ser ut til å være viktige i valget om å bytte. I tillegg belyser artikkelen problemstillinger knyttet til bruk av internett-panel og mulige skjevfordelinger av å bruke et forhåndsrekruttert panel.

Den tredje artikkelen analyserer prisspredning i standard elektrisitetskontrakter. Analysen tar som utgangspunkt at prisene for et homogent gode over tid vil konvergere i tråd med the law of one price". Altså at prisspredningen blir mindre over tid. Analysen er todelt: Først en deskriptiv fremstilling av dataene som gjør at vi forkaster hypotesen om at prisene konvergerer over tid. Videre analyse undersøker om det er tegn som viser at dynamikken på lang sikt indikerer noe om prisspredningen. Ved å bruke kointegrasjon som tar hensyn til ikke-stasjonære tidsserier, estimerer studien hvordan konsumenters bytteaktivitet, markedsprisen for elektrisitet og antall strømselskap som tilbyr de enkelte typer av kontrakter påvirker prisspredningen. Resultatene viser at bytteaktivitet har en negativ påvirkning på prisspredningen, mens antall selskap bidrar til en forsterking av prisspredningen i de enkelte kontraktene. Samtidig avdekker resultatene at det er andre forhold som også ser ut til å ha innvirkning på prisspredningen.

Den fjerde artikkelen undersøker om det er mekanismer som kan tyde på prissamarbeid eller markedsoppførsel som ikke er i tråd med sunn konkurranse. Fra et utgangspunkt med transparente priser via en offisiell prissammeligningsside, undersøker vi om det finnes spor som tyder på at en slik side brukes til å koordinere priser. For å undersøke dette bruker vi maskinlæring, nærmere bestemt en input-/output hidden markov-model. Resultatene viser spor som indikerer at strømselskap inntar roller som prisledere og prisfølgere. Det vil si at markedsprisen og marginen ikke nødvendigvis er avgjørende for prisjusteringene som blir tatt. En generalisering utover de funnene vi avdekker i studien, viser at det kan tyde på at høy grad av transparens i prisinformasjon muliggjør slik markedsadferd. Slike prissammenligningssider har blitt vel etablert som et ledd i å sikre lett tilgjengelig og pålitelig informasjon om elektrisitetspriser for å motivere konsumenter til å bytte til en gunstigere strømavtale.

Funnene bidrar med ny innsikt om markeds- og konsumentadferd og prisutvikling, noe som er nyttig når langtidseffektene av markedsreformen skal evalueres. Funnene tyder på at elektrisitetsmarkedet fungerer godt. Samtidig understreker funnene at det er viktige problemstillinger knyttet til markedsdesign, pristransparens og tilbøyeligheter i husholdningers avgjørelse om bytte av strømselskap. Sporene som indikerer priskoordinerende markedsadferd, bør ikke undervurderes når nye reguleringer skal implementeres for å sikre en effektiv langtidsutvikling av strømmarkedet.

# Introduction

# 1 Introduction and Background

Rising electricity prices bring about attention. Usually, the media cover such events and tend to link high prices to exports of cheap hydro power at the expense of residential consumers and squeezed households budgets. This happens because electricity is an essential good. Electricity covers needs such as heating, lighting, cooking, and access to Internet infrastructure. In addition, the massive switch to electric cars has added a supplementary use of electricity for transportation purposes. Recent numbers from Statistics Norway show that more than 50 percent of first-time registered passenger cars in 2020 were electric-powered.

As electricity expenses make up a substantial proportion of households budgets electricity should, from a normative economic perspective, encourage rational consumers to look for good electricity deals to keep expenses low, which in turn should control retailers who want to keep their margins high. However, figures from The Norwegian Water Resources and Energy Directorate (NVE) show that a large percentage of consumers do not switch to better deals. In addition, causal observations of electricity contract prices show a substantial variation in margins within similar contract segments. Both are factors that may violate the basic premises for a competitive market. Numerous efforts such as price transparency, elimination of any switch-related fees, and unbundling of retailing and network services have been made in order to ensure market efficiency, increase consumer participation and stimulate to retail competition.

Applying industrial organization theory and detailed empirical analyses, this thesis addresses and brings new evidence to bear on issues related to efficient market outcomes from the following perspectives: consumer behavior, price development in electricity contracts, and the existence of any facilitating practices for collusive market behavior. In addition, the thesis provides insight into the regulation of network companies and different incentive regulation models.

The thesis explores the above issues through four empirical papers. We study nearly two decades of electricity retailing, evaluate the long-run efficiency outcomes of the market reform and bring new evidence and insights to evaluate the performance of the retail electricity market.

The thesis discusses and answers four fundamental questions through the four chapters;

- The first paper, *Benchmarking in Regulation of Electricity Networks in Norway -An Overview*, provides a synopsis of the benchmarking models used in incentive regulation for electricity network companies. The paper investigates the specific issues that have driven the development of models in the three first periods of incentive regulation, how the results have been used, and outlines what we have learned. The paper offers a thorough discussion related to scale parameters and input/output parameters and choice of data measurement systems to provide insight into important aspects in incentive regulation. The paper summarizes these issues and discusses the potential effect such choices can have on efficiency scores and thus revenue caps for network companies.

- The second paper, *Household Choice of Electricity Retailer*, explores households' switch behavior from a perspective which takes into consideration that context matters for switch decision. Thus, adopts a theoretical framework hinging on Bansal et al. (2005) and the application by Ek and Söderholm (2008) that embraces both psychological and economic influences to induce switch decision. The study uses a survey dataset on households' preferences in electricity related issues and uses probit estimation techniques.

- The third paper, *Electricity Retailing and Price Dispersion*, examines price development in standardized electricity contracts from the point of view that prices for a homogeneous good should converge, according to the "law of one price". The paper investigates whether electricity prices for standardized electricity contracts (variable price, market price, fixed-price) converge according to this view. In addition, the paper explores the long-run dynamics of consumer switching, market price fluctuations, and number of firms offering the specific contracts on dispersion in electricity contract prices to create new insight into these factors as drivers for sustaining dispersion in prices. The study builds on well-established theoretical models to rationalize price dispersion in homogeneous product markets and adopts a novel empirical approach using a vector error correction model (VECM) framework to identify factors that rationalize a range of prices for similar contracts.

- The fourth paper, *Price Leadership and Electricity Retailing* explores market behavior among nationwide electricity retailers and investigates whether there are any signs of mechanisms for facilitating practices such as price leadership. The paper approaches this question by determining whether retailers mimic and follow price adjustments made by other retailers through a Markov chain model of price changes.

The research questions above relate to and expand upon previous work on the establishment of a spot price-based energy marketplace as presented by Bohn et al. (1984) and Schweppe (1988). It also relates to previous studies that describe the specific implementation of an energy marketplace in Norway. For example Midttun (1987) documents the performance of the current sector and the need to restructure to improve inefficiencies, and Bye and Johnsen (1995) simulate the efficiency effects of opening up the electricity market, specifically among the Nordic countries. In general, a substantial amount of work was done to evaluate the outcomes of the market reform the first years after the elimination of any switch related fees and the establishment of an official Web page to provide price information. For example, Amundsen and Bergman (2003); Amundsen et al. (2006); Bye and Hope (2006); Bye et al. (2003) and Littlechild (2006) evaluated the efficiency effects in the first years after fully opening up to competition, following elimination of any switching fees.

Studies by Barrett (2017); Hope (2005); Lewis (2008); von der Fehr (2013) and Vesterberg (2018) have evaluated market performance from the perspective of market design issues and consumer behavior. Looking back over some 20 years since fully opening up to electricity retail competition, this thesis evaluates the long-run development in electricity prices, electricity pricing strategies by retailers, and consumer behavior to learn more about the long-run efficiency outcomes of the market reform.

The subsequent parts if this introductory chapter are organized as follows. Sections 2-4 provide the essential background and context setting the stage for the chapters comprising the body of the thesis. This includes the policy work leading to market reform, presentation of early issues of concern, a distinction between the regulated and the market based parts of the sector and a presentation of the crucial premises for a competitive market. Section 5 describes the data. Section 6 presents the methods underpinning the present research. Section 7 summarizes the papers and gives a schematic overview of the scope of the research in Figure 1 and Figure 2. Finally, Section 8 summarizes key findings and provides concluding remarks.

## 2 The New Energy Act

Market orientation to improve efficiency, is from an economics perspective, the best overall approach for achieving efficient resource allocation and transferring benefits to consumers. To obtain such allocation in the electricity sector, certain crucial premises are required to make it work. Schweppe (1988) notes three fundamental criteria in this regard: definition of spot prices through various time periods, typically hourly prices, definition of electricity contract types, and rates; and implementation of the actual market with real-time calculation/prediction of spot prices, metering and billing, and a control center using the defined price as a control signal. Although this formula proposed by Schweppe seems straight-forward and in line with traditional market principles, the complex industry structure encompassing a set of distinct activities; including generation, high voltage transmission, lower voltage transmission, and supply to final consumers, means that market orientation of electricity sectors is a challenging exercise.

Nevertheless, there are certain principles that help make it work. First and foremost, it is crucial to separate potential competitive segments from those having natural monopoly characteristics. Next, it is essential to implement a good market design as well as efficient models for regulation.

In Norway, there were divergent philosophies on how to achieve a more efficient electricity sector. One idea was a step-wise approach to market reform by reducing the number of vertically integrated companies in generation, retailing and distribution of electricity from approximately 70 generation companies and 230 network owners with an extensive degree of vertical integration, to 20 regional vertically integrated companies. The alternative was to fully establish the market in one overall process Hope (2007).

Eventually, based on a framework for the establishment of an energy marketplace and the treatment of electricity as a commodity as outlined by Schweppe (1988), the concept of restructuring the Norwegian electricity sector evolved. Important studies in this regard included contributions by Midttun (1987) and Bye and Strøm (1987), which documented an overall analysis of the current electricity sector, in terms of both generation and regulation of electricity networks and prices. In general, these studies related inefficiencies to cost overruns in state-owned generation companies. In addition, inefficiencies were related to non-corresponding production capacity and marginal costs in state-owned companies.

However, it was not until the Ministries of Finance and Oil and Energy decided to commission a research project with aim of designing an analytical and theoretical framework for electricity market reform that the idea came close to realization. The project was carried out by the Center for Applied Research (SAF) and was led by professor Einar Hope under a mandate to analyze the possibilities for increasing efficiency in the electricity sector. With an overarching aim to develop a market-oriented distribution with rational economic players, public regulation principles, and policy measures aimed at the technical and economic nature of a hydro-power driven system. Contrary to the international trend toward privatization, it was clear from the outset that this was never considered as a means to liberalize the Norwegian electricity sector. The main reason for this was political, as strong traditions of social democracy and national ownership simply made privatization unacceptable to the Norwegian Parliament. Although there were many obstacles and different approaches to making such an efficiency improvement in the sector work, the eventual electricity reform was a result of comprehensive research work, including economists, lawyers, engineers, and bureaucrats.

The work led by Professor Hope's research group documented in Bjørndalen et al. (1989) can in retrospect be divided into two main phases stemming from divergent philosophies on how to achieve an efficient market: a first phase leading to a proposed law proposal that was never approved; and a second phase leading to a proposed law that was accepted.

Hope (2007) states that the first law proposal was only modest in adopting a market approach, and mainly hinged on the Norwegian Water Resources and Energy Directorate's (NVE) idea of achieving efficiency through a few large, regional, vertically integrated companies. Furthermore, Hope states that the discussions within the group centered around whether it was operationally achievable to introduce the massive structural changes that a full market orientation would demand. A realistic approach was therefore a more modest version of a market approach. However, this first attempt to restructure the electricity sector failed to get broad support. The first proposal was nevertheless an important step to further prepare, mature, and motivate important discussions among the industry as well as among politicians and government ministries.

The final law proposal that was issued in June 1990 and passed the same year, was more controversial in the sense that it adopted economic phrases and terminology, went much further in market orientation and included the main elements of the approach proposed by Schweppe (1988), adjusted and customized to the features of the Norwegian electricity sector:

- Establishment of power markets (spot, forward, futures, ancillary[1])
- Establishment of Statnet SF as a transmission system operator (TSO)
- Principle of common carriage in distribution, separation of retailing and transport by account
- Regulation and policy interventions relating to network companies (common carriers)

Numerous regulations to establish the new market orientation were introduced early on. First, an extension of the forerunner to the spotmarket, *The Norwegian Power Pool* (*Samkjøringen av kraftverkene i Norge*), was established in an attempt to bring the demand side, represented by the electricity retail segment, into the pool. The power pool was established in 1972 as a formally organized spot market among the power producers to balance the stochastic nature of hydro power production, (Bye and Hope, 2006). Another early attempt to establish a marketplace for electricity was a process

[1]One such support for the primary activities was the establishment of balancing markets to correct for imbalances between supply and demand from any transmission capacity constraints, or stochastic fallouts of generation or power line capacity.

to adjust planned and actual supply and demand to ensure a flexible system to handle any bottlenecks and unforeseen instability between network and market in a balancing market. To handle the risk aspect in the sector and to allow risk hedging, a futures market was established as to trade forward and futures contracts. Together, these three markets laid the foundation for the spot market for electricity, organized and administrated by an independent company, *Kraftsentralen AS*. In addition, Statkraft's double role was redefined by diversifying activities into two different branches; generation on one side and transmission on the other, later known as Statkraft and Statnett. From the structural perspective, the grid was organized as a two-level system, including the transmission grid and a regional grid.

Hope (2007) argues that a crucial element of the restructuring was to ensure common carriage to the network, to open it up for the introduction of competition in services supplied over the grid. Another important element in the reformed sector was the handling of former vertically integrated companies. Newberry (2000) argues that establishment of independent distribution networks calls for a vertical separation of the incumbent to avoid any exploitation of the incumbency advantage. In the Norwegian electricity sector, the former vertically integrated incumbents were separated by account. It was not until 2006 a legislative change made all vertical integrated companies having more than 100 000 customers obliged to split into separate legal entities. A recent revision of the legislation that took effect from January 2021 made it obliged for all vertical integrated companies having more than 10 000 customers to split into separate legal entities. Adhere to the previous discussion and controversies outlined in Hope (2007).

International trade was established as soon as the legislature was modified to account for handling of such trade. As a result of this, it did not take many years before a common Swedish-Norwegian electricity market was established as the first multinational power exchange on January 1, 1996. In later years, Finland and Denmark were successively included in the joint Swedish-Norwegian power market, NordPool. The Baltics joined in 2012 and 2013 and multiple Central Western European countries in recent years. This eventually established the market with the structure known today.

Numerous studies have evaluated the market reform in Norway. Following studies by

Bye et al. (2003); Hope (2005, 2007); Johnsen (2003); Moen (2007); Olsen et al. (2006); Rud (1990); von der Fehr et al. (2005); von der Fehr and Hansen (2010) and von der Fehr (2013), the overall experience of market reform must be considered a success. Simultaneously, the previous studies point to factors that add complexity in reforming such a sector.

The next sections give an overview of electricity network regulation, the different models and their inherent nature.

# 3 Regulation of Electricity Networks and Political Intervention

Following Newberry (2000) the general rule for achieving efficiency in network industries is competition where possible, and regulation only where unavoidable. Due to the natural monopoly characteristics of electricity networks, featuring large sunk costs and long life-times, regulation is necessary to reduce monopoly profits and ensure efficient outcomes. This theoretical off-set is, according to Decker (2015), a normative rationale for why regulation of electricity networks should be done. Whereas the only alternative to the normative regulation approach is extensive state ownership of utilities. Referring to Hope (2007), extensive state ownership was never considered in Norway due to the existence of many small municipality-owned distribution networks [2]. The authorities considered it to be neither realistic or desirable to acquire these locally owned networks in any form of extensive state ownership structure.

An issue of utmost importance in the regulation of electricity networks is making firms take actions that they would not otherwise do without regulation. A well-known obstacle to achieving such behavior is presence of asymmetric information. Thus, the regulated firm has an information advantage over the regulator. This issue is discussed by Caillaud et al. (1988) and Armstrong and Sappington (2007). More specifically, these studies relate information asymmetry to either hidden information (adverse selection) of costs kept by the firm or related to hidden actions (moral hazard),

[2] At the time of introduction of the market reform there were 230 network owners.

due to hidden information related to efforts to increase costs.

In Norway, there was awareness of potential asymmetric information issues from the outset, but there was no regulatory model to handle these issues. Neither the cost-plus regulation applied at the time of introduction of the new Energy Act, nor the rate of return regulation introduced a few years later involved incentives for regulated companies to be efficient. The hitherto latent potential for efficiency improvements through an incentive based regulation called for extensive research regarding the possibilities for embracing information issues and implementing a stronger incentive for networks to be efficient. In the liberalization of the Norwegian electricity market, this process was driven by research on one side and experience on the other[3]. Studies by Kittelsen (1993, 1994) and Førsund and Kittelsen (1998) were driving forces in this regard and laid the foundation for an incentive-based approach to regulation through Data Envelopment Analysis (DEA).

In total, the incentive regulation models has proved to be efficient; however, to further improve efficiency and overcome issues related to strategic behavior among network firms, a modified yardstick model was introduced from 2007. NVE adopted a modified version of the yardstick competition regulation model following Shleifer (1985) in 2007. From a theoretical view, yardstick competition seeks to compare cost levels among similar firms, which encourages firms to cut costs and improve efficiency. Amundsveen and Kvile (2016) provide a detailed account of modified yardstick-competition adopted by the Norwegian Water Resources and Energy Directorate in 2007. Moreover, a recent study by Senyonga and Bergland (2018) analyzes the efficiency and productivity of Norway's electricity distribution utilities during periods of incentive regulation and yardstick competition. Their results suggest that there have been significant improvements in technical efficiency after the regulatory change to yardstick competition and that improvements have been greater in relatively more inefficient firms/utilities.

[3] Wolak (2005) refers evolving process of learning, adjusting, and implementing as "Smart Sunshine Regulation", where the regulatory process evolves and becomes better as comprehensive information is gathered, which allows regulatory and political processes to detect and correct problems.

# 4 Premises for a Well-Functioning Electricity Retail Market

There are certain components that are fundamental to electricity markets; Decker (2015) provides a general schematic overview of the components of an electricity network industry, whereas specific overviews of the Norwegian electricity sector is provided by Bye and Hope (2005), Hope (2007), and Rud (1990).

From a market design perspective, the power system in Norway is comprised by markets that covers different operations; markets for trade in electricity[4] that defines the market equilibrium price for aggregated supply and demand schedules set for each hour; markets and instruments for risk hedging for market participants to manage risk and uncertainty about future prices[5], markets for investment in new capacity; markets for trade in environmental energy products such as green-certificates[6]; and a balancing market (short-term market) to correct for imbalances between supply and demand. Thus, following that the system price is determined without taking into account potential network capacity constraints such that the area price may be higher/lower than the market price determined at the pool. In the national retail market, retailers offer electricity contracts to end-user customers. Whereupon end-users are free to choose any contract from any retailer offering service in a given area without any switch fee. Thus, consumers are encouraged to choose a competitive contract as to discipline retailers to offer competitive prices and thus maximize welfare through a a resource allocative outcome. From a standard textbook in industrial Organization theory, such as Belleflamme and Peitz (2010), the following premises are considered crucial for a perfectly competitive market: homogeneous product; a large number of non-dominating market participants (on the demand and supply side); perfect information, and; no barriers to entry.

Nonetheless, a perfect competitive market with maximum transfer of benefits to consumers as outlined by the premises above, only exists in theory. The extent of market

[4]This market is an integrated day-ahead-market which accounts for more than 70 percent of the total volume.

[5]Futures, forwards, options and contracts for differences.

[6]A joint Norwegian-Swedish electricity certificate scheme started in 2012

imperfections such as market power, barriers to entry, asymmetric information, and externalities, will alter the perfect competitive outcome. Following Rud (1990), imperfections in the electricity market stems from different sources: some are inherent to the nature of electricity, while others are market-specific.

To evaluate the performance of a market, one needs to consider the existence and prevalence of elements such as structural design issues, existence of any biases in consumer decision-making, and factors related to facilitating practices that may be important in altering an efficient market outcome.

The next paragraphs examine the basic premises for a competitive market, and bring together the structural characteristics of the electricity retail market with an emphasis on product characteristics, market transparency, and potential sources of facilitating practices that may increase the likelihood of collusive market behavior.

### Homogeneous Good

Evaluated from the theoretical premise of homogeneous good characteristics, electricity is a 100 percent homogeneous product. That is, it cannot be distinguished according to quality due to its inherent physical product characteristics. Electricity flows in the system according to Kirchhoff's Current law, which states that the total current entering a circuit's junction (node) is exactly equal to the total current leaving the same junction. This is because it has no other place to go, as no charge is lost. Following this, electricity consumed at a given point in the system cannot be distinguished according to source of origin whether the electrons stem from a nuclear driven power plant, hydropower or alternative sources is impossible to know. Hence, electricity has a non-distinguishable quality from the physical perspective.

One perspective which challenges the view of electricity as a "pure" homogeneous good is that of "packaging" electricity into different contracts due to risk preferences and volatility of prices. Thus, from this perspective one may argue that electricity contracts can be considered as slightly heterogeneous products distinguished by consumers' risk preferences. However, from the research perspectives considered in this thesis, electricity is a homogeneous commodity within the different standardized contract segments, as the opportunities to differentiate the products were severely limited in the time frame of the study. This implies that, from a theoretical perspective, prices should not vary much within similar contract segments.

## Market Power

Exercise of any kind of market power is a source of market inefficiency and non-optimal allocation of resources. Starting from the theoretical rationale, market power can take two forms; unilateral or collusive. Unilateral market power is, using a standard economic definition, a firm's ability to raise its product price above the competitive level or the benchmark price defined in the short run (Motta, 2004). Such behavior can occur if a firm has a dominant market position but will in most cases be regulated and controlled though antitrust policies and market monitoring by Competition Authorities. Nonetheless, there are certain markets that are more prone to such market power due to specific market characteristics that make regulation and monitoring challenging. From the perspective of the Norwegian electricity sector Bye et al. (2003) and Hope (2005) emphasize that the electricity wholesale market (from a structural perspective) is potentially prone to unilateral market power due to a relatively low number of market participants and high barriers to entry. On the contrary, the closely related retail electricity market has very different market characteristics, which make unilateral market power a minor concern due to the numerous market participants and low entry barriers (thus, there are low start up costs to set up a new electricity retailing company). In contrast, collusive market power (explicit or tacit) is more likely to occur in the retail market due to frequent interaction among retailers and transparency in price information. Hence, from which on may argue that the market structure is prone to mechanisms that facilitate collusive behavior which enables retailers to raise prices above the competitive equilibrium.

## Transparency in Prices

Although one may argue that transparency potentially brings in a "dark side" to the electricity retail market, ready and available information about electricity prices and abolishment of any switching fees, have brought about prerequisites as to ensure and motivate consumer participation in the market place. Because, as stated in Gamble et al. (2009) and pinpointed in numerous studies on consumer participation in deregulated electricity retail markets, consumers failing to search for and choose the best deal may be a source to jeopardize the efficiency of deregulated markets. Thus, high switching rates and consumers with an inherent conscious awareness of prices contribute to competition among retailers and market efficiency. Thus, switching rates can be an indicator of the success of market deregulation and should not be underestimated as an important tool to improve market performance along with competitive retail prices. Even so, conditions related to market transparency were debated early in the process of setting up and structuring the electricity retail market for reasons already mentioned.

In this market mandatory reporting of electricity price information to an official Web page set up in 1998 was one early attempt to ensure transparency on electricity contract prices and contractual terms. At the time, this attempt to make reporting of prices mandatory gained massive attention in national and international media, as it was a unique measure in such a market from a worldwide perspective. Johnsen (2003) argues that the impact of this massive media coverage should not be underestimated as an important contributing factor to a shift in the number of households that switched retailers and contracts in the first years after the introduction of the comparison site. Thus, as an important attempt and nudge to ensure consumer participation, Johnsen's point supports the traditional view, which recognizes informed consumers and market transparency as crucial aspects in achieving market performance, from the consumer perspective.

This thesis takes into consideration the "dark side" of price transparency; As first put forth by Stigler (1964), transparency in prices represents an opportunity for retailers to observe and adjust. Thus, more information can potentially facilitate non-competitive practices and thus be vulnerable to collective market power. This is exactly what the study by Albæk et al. (1997) find. More specifically, the study provides empirical support for how more transparent price information for ready-made concrete in Denmark significantly increased prices. A few previous studies discuss this issue from the perspective of the deregulated electricity markets. Bye and Hope (2005) put forth the question in relation to the price information system of the Norwegian Competition Authority (NCA) "..perhaps the market has become too transparent". Furthermore, Hope (2005) argues that due to the generally high degree of market transparency in electricity markets, it is worth investigating whether the markets are in fact transparent to facilitate the exercise of collective market power and tacit collusion among suppliers. Additionally, von der Fehr (2013) discusses relevant issues related to the European Union's introduction of a new regulation on the submission and publication of data in electricity markets. Von der Fehr brings together four main reasons why increased transparency might reduce market efficiency: (1) New market information will only be adopted if it can improve good market decisions by firms, hence not all new information will be considered relevant in this respect; (2) Mandatory reporting of sensitive information can lead firms to distort or conceal information; (3) Increased availability of information can encourage tacit collusion and undermine competitive behavior, as noted in the findings of Albæk et al. (1997); and (4) The process of gathering, processing, and disseminating information is costly, and costs must be evaluated against the utility of transparent price information. Overall, the study by von der Fehr argues that more information is not always better from a competition perspective for electricity retail markets.

This thesis expands upon the existing literature on price transparency and explores whether accurate and timely information about the pricing behavior of all retailers provided through the price comparison site hosted by NCA facilitate any collusive behavior. Hereunder, if there are any price leaders in this market.

The thesis goes further than previous work in the field by studying how retailers adjust prices by observing other retailers' price adjustments from a machine learning approach. This methodology has not yet been adopted to study strategic pricing in the Norwegian electricity market or any other liberalized electricity retail markets, as far as the author is aware.

# 5 Data

As already stated, this thesis comprises four papers. The first provides an overview of various regulation models during three periods of incentive regulation. The remaining three papers analyze efficient market outcomes from three distinct perspectives: consumer choice, price development, and collusive market behavior among retailers.

The three papers that evaluate market outcomes are underpinned by four datasets: time series data on electricity prices from NCA; survey data on consumer preferences in electricity related issues and data on retailer switches performed by households, both from NVE; and electricity market price data from NordPool.

The dataset from NCA was assembled as a result of mandatory reporting of electricity prices for the so-called standard electricity contracts, determined by the Standard Agreement from 1997. The dataset includes prices for the standard variable contract, market price contract, and fixed price contracts (1 and 3-years' duration). In addition, the dataset provides detailed information on price adjustments and effective dates for proposed price changes. Extended information on effective dates for price changes are vital to address the research question related to collusive behavior.

The thesis uses two distinct versions of the price data obtained from NCA. The first version includes all price observations, which allows a rich diversification of price development in the specific time frame for the study, 2004-2015. During this period, standardized contracts were considered homogeneous due to limited opportunities for retailers to diversify products within the predefined contract types. In later periods, this changed as a great variety of services and products were combined, which eventually resulted in a more diversified product segment within each standardized product segment. This rich dataset on electricity contract prices provides an opportunity to explore well established models to rationalize price dispersion.

The second version of the dataset is used in the fourth paper, which explores retailers' market behavior. Here the actual dataset used is somewhat selective due to the research purpose. Thus, the data comprises nationwide retailers or prominent regional retailers having a nationwide profile. Due to substantial entry and exit of retailers during 2000-2010, the period for which we were able to construct a continuous series with daily price history was between 2005 and 2009. Retailers offering any prepaid-contracts are excluded. In addition, the study adopts the market price obtained from NordPool. The time frame of the study is 2004-2010.

IPSOS MMI collected the survey dataset for NVE between January 24 and February 11 2013. The authority carried out the extensive survey in an attempt to gain new insights into households' adjustments, knowledge, and awareness related to their own electricity consumption. The sample of 1108 respondents was drawn from a pre-recruited internet panel of 50 000 individuals, stratified according to age, gender, and education. Respondents were asked numerous questions about electricity-related habits, preferences, and attitudes towards environmentally related issues as a motivation to reduce electricity consumption. In addition, some questions covered socio-economic variables. The dataset is rich, and provides detailed information about the population and its electricity-related habits.

There are a few issues that need to be addressed related to the use of such datasets in scientific papers. On the one hand there are a number of advantages associated with using an Internet panel for surveys, including cost effectiveness and the opportunity to reach a large number of respondents. Additional advantages are shorter turnaround time relative to traditional surveys and an instant update of the database as respondents complete the survey. However, there is a downside related to a pre-recruited internet panel.

A study by Tsuboi et al. (2015) found that the estimated characteristics of commercial Internet panel surveys were quite different from the national statistical data, reflecting a problem of external validation of the results outside the population of the Internet panel. This methodological issue is highly relevant and must be borne in mind when interpreting results in this study. It is especially important to be aware of the potential bias imposed by questions of a technical nature. Such questions can potentially impose skewness in the sample relative to the population the sample is supposed to represent. In this survey there are several questions related to households' skills in searching for information online. The importance of this potential bias should not be underestimated.

In addition, one should be aware that respondents who are part of an Internet panel may be engaged in a variety of reward programs for participating in surveys (Hays et al., 2015). This may potentially undermine the data integrity.

This concern needs to be considered when generalizing results to the wider population for the purpose of policy design recommendations. NVE has not made any attempt to modify survey results in their report from their internal study on consumers' activity in the end-user market for electricity.

# 6 Methods

The thesis uses established methods to evaluate market performance from the already mentioned perspectives, ranging from a basic probit framework to more sophisticated methods such as machine learning and cointegrated vector error correction models.

The first article, on the regulation of the electricity network, provides a critical overview of the benchmarking models, including the application of their results in the first three periods of incentive regulation after the introduction of such regulation in 1997. The paper discusses specific issues relating to the development of the DEA models. From an overarching view of the various model specifications and the issues driving their development, the paper argues that thorough knowledge about cost structures and cost drivers is required to achieve the goals of the incentive regulations.

The second paper on households' choices, adopts a probit model for binary response to explain the effects of the independent variables on the probability of the average respondent switching electricity suppliers. The model characteristics are such that the standard normal cumulative distribution function (cdf) is strictly between zero and one for all parameters (Wooldridge, 2016). The full model determinants were obtained using a backwards reduction approach. Furthermore, a general-to-specific (GETS) approach following the logic described by Hendry and Krolzig (2004) and Campos et al. (2005) was used to support the choice of variables. This approach suggested the overall same model as did the backwards reduction approach.

The third paper, on price development in electricity contracts, uses a cointegration framework for estimation, inference, and interpretation to deal with variables that are not covariance stationary to enable identification of the economic relationships among the variables, focusing on long-run relations. Using multivariate system of variables, the paper reformulates a vector autoregression model to a vector error correction model (VECM) through rank reduction to estimate the long-run relationship among variables in the model and to quantify the effect from switching, number of firms offering a specific contract, and price adjustments on dispersion in electricity contract prices. This approach provides an opportunity to identify potential differences between contracts in how and to what extent price dispersion is affected by changes in switch volume, adjustments in the market price, and number of firms offering a specific contract. The results indicate and distinguish rigidity differences among variables, enabling evaluation of possible mechanisms to explain dispersion in prices.

The fourth paper adopts a machine learning (ML) approach to evaluate potential collusive pricing behavior among retailers. It uses an input-output hidden Markov model (IOHMM), first adopted in econometrics by Hamilton (1989). In general, ML is a way of applying algorithms to build mathematical models based on sample data, relying on pattern detection and statistical inferences. There are different types of machine learning algorithms in use, depending on the task the algorithm is designed to solve. One such task may be described as determining how to paint a whole picture when your view of the problem is only partial. In other words, among a set of unobservable, or not easily detectable states a system can be in, we can determine those states from other observable factors. This is precisely what the Hidden Markov Models (HMMs) are designed to do:

A Markov model $M$ is a type of random process described by a set of possible states $S = s_1, ..., s_N$ and a transition probability matrix where $a_{ij} = P(s_{t+1} = j|q_t = i)$ and $s_t$ denotes the state at time $t$. A random walk of $m$ steps starting from state $q_i$ provides a sequence $SEQ_m = q_i, ...q_{i+m}$ of states visited. Assuming the states are observable, we can calculate the probability of such a sequence of states being visited by multiplying the transition probabilities for each of the observed steps. In a Hidden Markov Model (HMM), we still perform random walks between states. What is different is that we cannot know which state preceded the present state. Thus, the random walk (i.e. the Markov chain) between states cannot itself be observed; only the outcome of the transition from one point in time to another point in time is apparent.

From a set of known output sequences of steps between states, one can estimate the likelihoods of each possible observation given all possible hidden states. These are called the emission (or output) probabilities. From the observable outcomes, it is then possible to calculate the most probable corresponding hidden states. HMMs can be applied to recover a data sequence of probabilities that is not observable by analyzing other observable data directly dependent on that sequence. Fields that typically apply HMMs include speech recognition and machine translation, computational biology (including DNA sequences and protein folding), and transportation forecasting.

HMM has the capability of learning the distribution of the output sequences. Building on this fact Bengio and Frasconi (1995) formulated the IOHMM architecture, based on expectation maximum (EM) estimation. This architecture maps input sequences to output sequences, expanding upon the HMM-approach by using the output sequence distribution only.

The essential aspect of the IOHMM is that a sequence of price observations can be mapped to a sequence of hidden states or labels. Moreover, the algorithm computes and assigns a probability distribution to each sequence of labels. This Bayesian approach allows us to determine the probability that prices set by retailers can be linked to a specific predefined hidden state. This includes variation of beliefs about parameters in terms of fixed observed data in order to determine the probability that a price adjustment stems from collusive behavior or is the result of an adjustment in the underlying market price.

In electricity market studies, the IOHMM approach has typically been used for forecasting electricity prices in the day-ahead market. A number of studies have adopted this approach, including those of Aggarwal et al. (2009); González et al. (2005); Kumar et al. (2016) and Mandal et al. (2017). These studies provides examples of how different versions of the IOHMM are adopted to forecast electricity prices in a market setting that has unobservable information about states.

However, the IOHMM approach has yet not been used to assign probabilities that price adjustments made by electricity retailers stem from collusive behavior in order to detect signs of market power in electricity retail markets. This thesis introduces the IOHMM approach as a method to analyze potential collusive behavior among retailers in the Norwegian electricity retail market.

# 7 Summary of papers

- Paper 1, *Benchmarking in Regulation of Electricity Networks in Norway - an Overview*, examines the origins of the natural monopoly characteristics of electricity network utilities and the demand for sound and reasonable regulation to secure necessary investments in the network, cut costs, and keep prices low. The paper gives an overview of the benchmarking models used in Norwegian incentive regulation from 1997- to 2011 and discusses the development of the DEA models, including the choice of scale assumptions and input and output variables, and also examines how the results from the benchmarking models are used. This is translated into revenue caps or income frames. Due to the considerable effects that model specification and data measurement choices can have on efficiency scores, and thus revenue caps, the paper emphasizes the crucial importance of a thorough knowledge of the cost structures and cost drivers of the industry. The paper concludes that in order to achieve the goals of incentive regulation, some adjustments to the benchmarking results may be necessary.

The three remaining papers analyze efficiency aspects from the perspective of the existing electricity retail market. With regard to consumers' activity in the market place, price development in electricity contracts, and facilitating practices of collusive market behavior among retailers. The papers provide new insights into market performance and efficient expansion of the sector in the long run as well as efficient use of available electricity resources in the short run.

- Paper 2, *Household Choice of Electricity Retailer*, explores the important determinants in households' decisions to switch electricity retailers. The analysis uses a theoretical framework that embraces both economic and psychological influences to induce households' switch decisions of electricity retailer. By running a detailed survey dataset on households' preferences in electricity- related issues in a probit model framework, the study finds that issues related to both market design issues and psychological factors seem important in determining switch choices. In addition, although beyond the scope of the results, the paper sheds light on issues related to sample selection and potential self-selecting bias in Internet panels.

- Paper 3, *Price Dispersion in the Norwegian Electricity Market*, examines price development in standardized electricity contracts from the view that prices for a homogeneous good should converge according to the "law of one price". From a theoretical approach using a clearinghouse model, incorporating data on the volume of households switching their electricity contracts, the market price for electricity, and the number of firms offering specific contracts, the paper adopts a cointegrated VAR-framework to estimate the long-run effects of switching, market price, and number of firms on dispersion in prices. The results show that prices do not converge. Furthermore, the study finds that both switch activity and number of firms offering a specific contract are significantly reflected in price dispersion. In addition, a modest but significant trend indicates that it is plausible that factors outside the model may explain some of the dispersion in prices. The paper highlights the importance of looking beyond the seemingly well functioning market as to facilitate an efficient expansion of the sector in the long run.

- Paper 4, *Price Leadership and Electricity Retailing*, takes the approach of accurate and timely information provided about the pricing behavior of other retailers through an official Web page. The paper analyzes existence of any facilitating behavior that resembles price leadership/following by adopting a sophisticated IOHMM framework. Results indicate an asymmetry in retailers pricing strategies and find that retailers differ in how prone they are to enter a different pricing state following an adjustment in margin size. In addition, results suggest that some retailers are more prone to shift pricing strategy following an adjustment in margin size than others. In addition, it is clear that certain retailers seem to hold positions as leaders/followers and that some exhibit pricing strategies that resembles that of barometric leaders/followers.

  Findings contribute to new insight about the "dark side" of price transparency in electricity retail markets. Moreover, findings in this study sheds light on price transparency and pricing strategies from of one of the first electricity retail markets.

The context for this thesis is presented in the previous sections. Figure 1 provides an overview of the scientific contributions of the thesis in that context. From Figure 1, it is evident that the main contributions of this thesis emerge from four papers which individually cover four different aspects of the evaluation of the performance of the retail electricity market and the regulation of network companies.

The more detailed overview in Figure 2 presents the objectives and findings in the papers comprising the thesis.

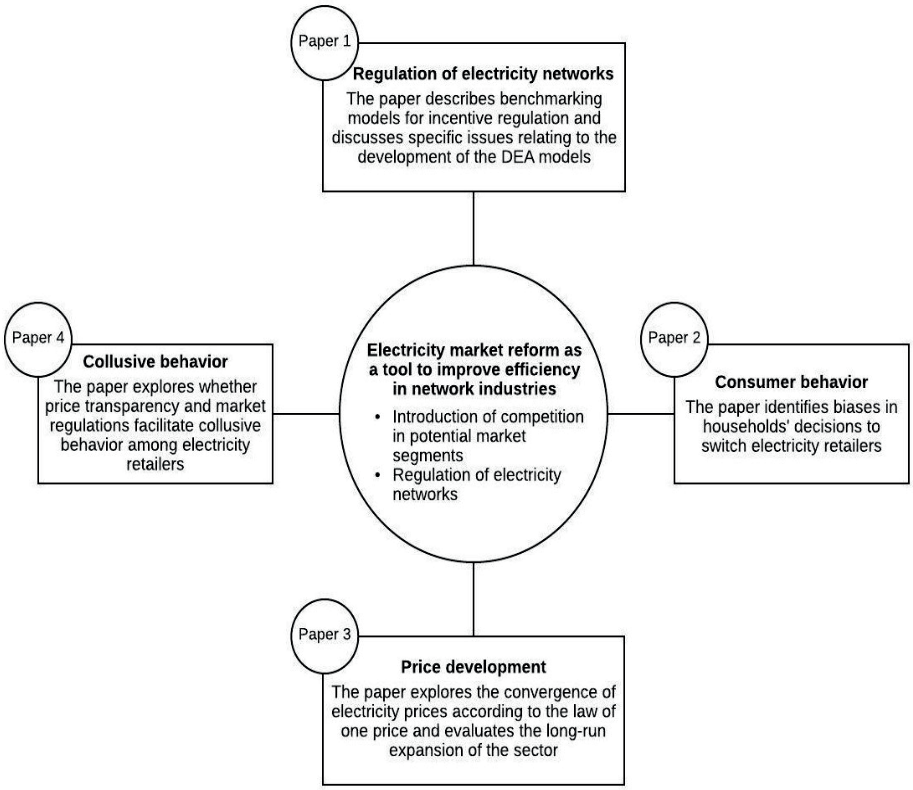


Figure 1: Papers comprising the thesis

| Paper | Objective/Research questions | What paper does | Theory | Data | Methods | Key findings |
|---|---|---|---|---|---|---|
| 1 | Provide an overview of the benchmarking models used in incentive regulation of electricity network companies. | Discusses specific issues relating to the development of the DEA models: choice of scale assumptions, input/output variables, and use of results from models translated into revenue caps. | | | Overview/ review | To achieve the goals of incentive regulation some adjustments (scale assumptions, input/output variables) are necessary. |
| 2 | Pursue a better understanding of households' propensity to switch electricity retailer. | Identifies any effects influencing households' decision to switch retailer from a perspective, which comprises both the economics and psychology of switch behavior. | Adopts a theoretical framework hinging on Bansal et al. (2005) that embraces both economic and psychological influences in households' switch decision | -Survey data on households' preferences in electricity related issues collected for NVE in 2013 | Probit framework | Issues related to both market design and psychological factors are important to rationalize switch decision. |
| 3 | Explore convergence of electricity contract prices according to the law of one price. Determine whether/to what extent switch activity, market price fluctuations, and the number of firms offering a specific contract affect dispersion in prices | The study explores price development in the electricity retail market to evaluate the efficiency of the long-run expansion of the sector | Refined models to rationalize price dispersion in markets for homogeneous goods with a price comparison site. Prices for homogeneous goods should not differ much. | -Electricity contract prices from NCA -Electricity Market price from NordPool electricity -Quarterly data on switch volume electricity retailers from NVE | Cointegration framework for estimation and vector error correction models | -Prices are not converging. -Switching and number of firms are significantly reflected in price dispersion -Significant trend parameters indicate that there are potential factors outside the model that may sustain dispersion in prices |
| 4 | Provide new insight into pricing strategies in the Norwegian electricity retail market | Explore whether price transparency and market regulations facilitate collusive market behavior such as price leadership | Dynamic models of oligopoly and market facilitating practices | -Electricity contract prices from NCA -Electricity market price from NordPool Spot | Input Output Hidden Markov Model framework (IOHMM) | Margin is not uniformly significant in determining price changes. Results indicate a pattern of facilitating market behavior: Price leaders and price followers |

Figure 2: Snapshot of papers comprising the thesis

# 8 Summary of Findings, Empirical Implications and Conclusions

The thesis addresses and answers the following questions:

1. What specific issues have driven the development of models in the three first periods of incentive regulation, and how have the results been used? What have we learned?
2. Are households' switch behaviors induced by both economic and psychological influences?
3. Do electricity prices for standardized contracts converge according to the "law of one price"?
4. Are consumer switch activity, adjustments in electricity market price and the number of firms offering a specific type of contract significant in affecting price dispersion?
5. Do retailers mimic and follow price adjustments made by other retailers?
6. Are there any price leaders in the retail electricity market?

From the overview paper on benchmarking models, the main conclusion is that in order to specify reasonable DEA models, thorough knowledge about the cost structures and cost drivers of the industry is required. To achieve the goals of incentive regulation, some adjustments may therefore be necessary. The results underpin the importance of more novel data developing better model specifications. Joskow (2014) refers to this process as "smart sunshine regulation", as better and more comprehensive information allows regulatory and process to detect and correct problems. Our findings suggest such improvements.

Estimation results from the probit model indicate that households' propensity to switch decision are influenced by both psychological and economic motives. More specifically, the findings reveal that issues related to both market design, psychological factors, and specific status quo biases that are important in determining switch choice. In general there seems to be a status quo bias related to incumbent retailers and issues related to billing practices. This is not controversial per se, but is nonetheless of great importance because active consumers are a crucial factor in competitive retail markets. Passive, or loyal consumers, can fail to penalize retailers with high margins, and thus contribute to sustaining dispersion in prices. One limitation of the study is the potential self-selection bias in internet panel surveys. The work sheds light on these issues and discusses limitations that may have influenced the results.

The results from the price dispersion paper indicate that prices for standardized electricity contracts do not converge according to the "law of one price". Furthermore, the results show that both switch activity and the actual number of firms offering the specific contracts are significantly reflected in dispersed contract prices. However, the results are not uniform across contract segments. In addition, the results show a modestly significant trend parameter, which may indicate that there are additional factors outside the model that drive dispersion in prices. One possible explanation may be the existence of mixed pricing strategies or of some kind of collusive market behavior. As the market is "maturing" there may be a "settling" into roles as price leaders, market share hunters or nurturers of a small group of loyal customers. This emphasizes the importance of looking beyond the seemingly well functioning market to correct for and gather new and more sophisticated insights into potential sources of market imperfections.

This is exactly what the fourth paper on price leadership does. The results from this paper show that some retailers are more prone to be price leaders and followers for price increases and price decreases. Thus, we find patterns indicating that specific retailers possess positions as price leaders and that differences in margin sensitivity for price changes are extensive.

Thus, results suggest that there are other motivations than margin squeeze that seem to explain adjustment in prices. We argue that price transparency potentially enables such behavior due to the ready and available prices at the official price comparison site. Specifically, we observe that certain retailers seem to systematically adopt information to control a specific market position. Thus, results add to the earlier suspicion that there are patterns indicating that specific retailers possess positions as price leaders in this market. Thus, hold positions as barometic and/or strategic leaders.

## Policy Implications

The thesis makes several contributions to the literature in the field of restructured electricity markets: by examining the regulation of electricity networks, facilitating practices among retailers, consumer behavior, and price development the thesis sheds light on issues that affect the performance of the sector.

Due to the complex structure of the electricity network industry, care should be taken in aligning findings to specific policy recommendations. However, the thesis contributes to new insights into certain crucial elements for efficient resource allocation stemming from market design decisions.

With regard to the regulation of electricity network companies, the thesis reveals that it is essential to have a thorough knowledge of the cost structures and cost drivers of the industry in order to achieve the goals of incentive regulation. The results emphasize the importance of a dynamic approach to achieve the intended efficiency goals in regulation.

This thesis also finds that electricity contract prices are not converging according to the law of one price, which emphasizes that there are factors in this market that affect and alter prices, allowing seemingly homogeneous products to differ. Consumer resistance to switching and market design issues are plausible explanations that call for a better understanding of market dynamics in order to adopt policy interventions to target market performance. From the perspectives of market transparency and market performance, the thesis provides insight into how price information from the official price comparison web page is used to facilitate market behavior among retailers. Results reveal pricing patterns, which indicate that certain retailers are more prone to be price followers and some retailers are price leaders. Detailed and timely information about effective dates for price adjustments on the official price comparison site enables retailers to systematically adopt information to control a specific market position. These findings enter the ongoing debate about the desire to increase information transparency in the electricity sector in the EU, as discussed by von der Fehr (2013).

The current results support a previous study by Hope (2005), which contends that it is worth investigating whether the electricity markets have become too transparent, facilitating the exercise of collective market power through coordinated actions.

Looking at market design issues related to traditionally vertically integrated companies, findings support that factors associated with vertical integrated companies seem to have strengthened biases towards the status quo among household consumers. Thus, results of the current study indicate that the inherited privileges of incumbent retailers seem to have impeded the free movement of consumers from the incumbent to a more competitive deal.

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# Paper I

# Benchmarking in Regulation of Electricity Networks in Norway – An Overview

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**Abstract** In this paper we give an overview of the Norwegian regulation of electricity networks after the Energy Act of 1990 and the deregulation of the electricity markets in 1991. We concentrate on the regulatory oversight of distribution network companies and regional transmission. Our main focus is on the benchmarking models, including the application of their results, in the three periods of incentive regulation that we have seen so far, after its introduction in 1997. We examine the various data envelopment analysis (DEA) models that have been used, and we describe specific issues driving their development and how the results have been used.

## 1 Introduction

In Norway, the Energy Act came into force January 1st, 1991, and laid the foundation for market based production and power trading. Transmission and distribution were considered natural monopolies and remained regulated. The Norwegian electricity sector was deregulated, but never privatized, and the companies within the electricity sector are still, to a very large extent, under public ownership. An essential part of the restructuring of the industry was vertical separation of business activities exposed to competition and regulated operations, i.e. power production and trading on the one hand, and power transportation on the other hand. Statkraft, the major state owned power company, holding a large part of the national power production capacity, high voltage transmission network, and system operation, was split to form the generation company Statkraft, and Statnett, the system operator of the Norwegian power market, and owner of the main part of the transmission grid. Statkraft and Statnett are both owned by the Norwegian state. For other electricity companies vertical separation has been implemented by separation of accounts, and both regulated and non-regulated activities can be accomplished within the same companies. The competitive business segments include generation of power, power trading and retailing, and also for instance alarm services, broadband and district heating. Network services and system operation are regulated by NVE, the Norwegian Water Resources and Energy Directorate.

In this paper we consider the regulation of the distribution and regional transmission companies, we do not consider the regulatory oversight of the main transmission owner and system operator, Statnett. The main part of the paper describes the development of the benchmarking models that have been used since the introduction of incentive regulation in 1997, in order to determine efficiency requirements for individual companies when setting their allowed revenues. However, in the following we first give a short description of the main elements of the regulation models for the three periods of incentive regulation that we have already seen, and then, after a general introduction to Data Envelopment Analysis (DEA), we treat some specific issues with regard to the DEA models that have been used by the Norwegian regulator, NVE.

## 2 Regulation of electricity networks after the Energy Act of 1990

During the first years after the Energy Act of 1990 and the starting point of the deregulation of the Norwegian electricity market, a rate of return (RoR) regulation was established from 1993. The main issues in this period were to determine book values of network assets in, for the most part, publicly owned firms and an appropriate cost of capital. The former was determined to a large extent on the basis of new values, whereas the latter was established on the basis of a capital asset pricing model (CAPM) framework. But, already in 1997 a new regulation model was introduced, with more focus on providing incentives for cost efficiency in the development and operation of network assets and services.

The incentive regulation starting in 1997 has been based on total cost, since treating operating and capital costs differently may result in adverse incentives, as there are substitution possibilities among the two cost groups. Moreover, the incentive regulation has been implemented as a revenue cap, i.e. a maximum allowed revenue for individual companies. This is reasonable, since costs are mostly fixed, i.e. vary little with respect to transported volume, and demand for network services, which is a derived demand, is quite inelastic. Regulation by price caps was discussed before the regulation period starting in 2007 (e.g. von der Fehr et al., 2002), but was not adopted. With fixed cost and inelastic demand, and assuming no ex post adjustments due to volume, the question of price or revenue caps is to a great extent a question of who is to bear volume risk, companies or customers. With a revenue cap it is the customers who bear the volume risk.

The regulation of the network companies is an ex ante regulation with some ex post adjustments, and the process is structured as follows. Before the period for which the allowed revenue is to be determined, cost data and information about company inputs and outputs are collected. This information is used to evaluate the relative efficiency of companies. Together with updates on prices, interest rates and possibly the level of activity of the companies' operations, total cost and efficiency results are used to settle on revenue caps for individual companies. Finally, after the period, when prices and cost are known, allowed revenues are adjusted. Adjustments may also be made due to limits on maximum and / or minimum accounting rates of return.

Since 1997 there have been three periods of incentive regulation:

- Period I: 1997-2001
- Period II: 2002-2006
- Period III: 2007-2011

In Figure 1 we show some economic figures on aggregate level for the period 1997-2009. We show total revenue caps for distribution and regional transmission networks, and the corresponding revenue per unit of delivered energy (NOK/KWh).

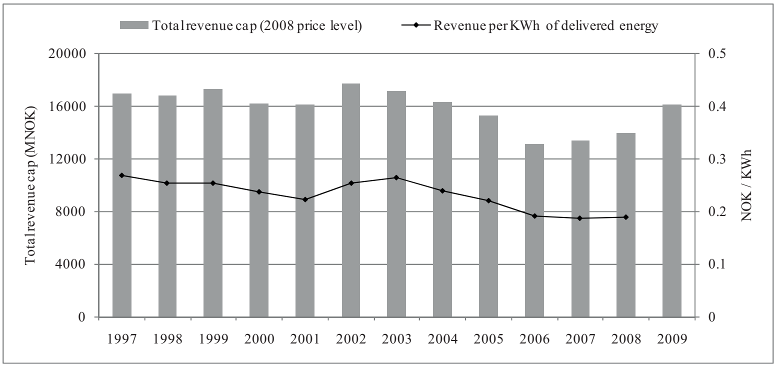



**Figure 1.** Revenue caps for distribution and regional transmission.

In the following, we describe some of the main elements of the Norwegian regulation of electricity distribution (mostly ≤ 22 kV) and regional transmission (mostly between 22 and 132 kV) during these three periods.

## *2.1 Period I: 1997-2001*

In the first period of incentive regulation, total cost was based on accounting values from 1994 and 1995, and this was the starting point for calculating company specific revenue caps for the whole period from 1997 until 2001. Within the period, the revenue cap was adjusted annually for inflation and changes in the energy prices (to account for power losses), for general and individual efficiency requirements and for increases in delivered energy in the concession area of the company. The revenue cap in 1997 was

$$Rcap_{1997} = C_{1997} \cdot (1 - X_g)$$

where $C_{1997}$ is the actual cost from 1994 and 1995 adjusted to 1997 price levels, and $X_g$ is a general efficiency requirement of 2 %. The update of the revenue cap from year $n$ to $n$+1 was then accomplished through the following formula

$$Rcap_{n+1} = Rcap_{n,\ price\ adjusted} \cdot (1 + \frac{\Delta DE_{n,n+1}}{2}) \cdot (1 - X_{g+i})$$

where $\Delta DE_{n,n+1}$ is the percentage increase in energy delivered from one year to the next in the concession area of the company, and $X_{g+i}$ is the sum of a general (1.5 %) and individual efficiency requirement. The individual efficiency requirement was determined from DEA, and it was assumed that about half the inefficiency potential should be caught up with over the regulation period. The compensation for increases in delivered energy was introduced to account for necessary increases in cost due to new activities, and this constituted approximately 300 mill. NOK annually for the whole industry.

In 2001 a quality mechanism based on the value of lost load (VOLL) was introduced in the regulation. In this period, the quality mechanism represented an adjustment of the revenue caps, and this could be positive or negative. Expected VOLL was computed for each company, partly based on historical data and partly from model results. Any difference between actual and expected VOLL was charged or attributed to the companies.

Finally, minimum and maximum average accounting rates of return for the whole period applied, and they were set to 2 % and 15 %, respectively.

## *2.2 Period II: 2002-2006*

The second period of incentive regulation was structured similarly to the first. Total cost was now based on accounting values from 1996-1999, and this formed the starting point for calculating annual revenue caps for 2002-2006. For 2002 the revenue cap was

$$Rcap_{2002} = C_{2002} \cdot (1 - X_{g+i})$$

where $C_{2002}$ is total cost from 1996-1999 adjusted to 2002 price levels. Average operating cost and 1999 depreciation were adjusted by the consumer price index, while average network losses in MWh were evaluated at a reference price for energy for 2002 determined by NVE. Interest was calculated from depreciated book values at the end of 1999, and with a regulated interest rate that in period II was updated annually. $X_{g+i}$ was the sum of a general (1.5 %) and individual efficiency requirement, the latter found by DEA, as in period I.

Within the period, the revenue cap was updated annually for inflation, changes in energy prices and interest rates, and for general and individual efficiency requirements. The revenue cap of year *n* in the 5-year regulation period was

$$Rcap_{2001+n} = C_{2001+n} \cdot (1 - X_{g+i})^n + CP_n$$

where $C_{2001+n}$ is actual total cost from 1996-1999 adjusted to year 2001+*n* price levels, and $CP_n$ is a compensation parameter for new investments. In regional transmission the compensation parameter was based on actual new investments, whereas in distribution the compensation was accomplished by an index depending on new customers connected to the grid and the national increase in delivered energy. The compensation for new investments constituted approximately 200-300 mill. NOK annually for the whole industry in period II.

The quality mechanism was refined, but worked otherwise mostly as in period I, although, as we will describe later, it was also included in the benchmarking models. The minimum and maximum average accounting rates of return were 2 % and 20 %, respectively.

## *2.3 Period III: 2007-2011*

Although the long time horizons of the first two regulation periods gave strong incentives for cost efficiency[1], the same long time horizon had an adverse effect on investments. It took a long time before depreciation and interest for new assets were accounted for in total cost, and this could have severe effects on the net present values of new investments (Bjørndal and Johnsen, 2004). In the third regulation period we therefore saw some major changes, especially related to annual updates of cost and efficiency requirements, the latter taking the shape of cost norms from the DEA benchmarking. Thus, from 2007 annual revenue caps are established for individual companies based on a combination of actual cost and cost norms, according to the following yardstick formula:

$$Rcap = C + \rho(C^* - C) = \rho C^* + (1-\rho)C \,, \qquad (1)$$

where $C$ is the actual cost, $C^*$ is the cost norm, and $\rho \in [0,1]$ is a factor that specifies the strength of the incentives in the yardstick model, i.e. the weight that is attributed to the cost norm.

For 2007 and 2008, $\rho$ was equal to 0.5, but from 2009 on, it has increased to 0.6. Actual cost and cost norms are updated annually, although, in practice, due to accounting procedures and the need for securing the quality of the data, up until now there has been a time lag in the application of cost data. More specifically, for 2007 and 2008 the cost data used for calculating actual cost and analyzing relative

[1] There could however also be ratchet effects, since total cost formed the basis for revenues in the *next* 5-year period.

efficiency were 2 years old; i.e. the actual total company cost $C$ estimated for year $t$ consisted of a combination of registered and calculated costs, based on accounting values[2] in year $t$-2.

For distribution companies and regional transmission companies, the cost norm, $C^*$, is calculated based on relative efficiency scores found by DEA. There are still separate DEA models for distribution functions and regional transmission / central grid functions, respectively. A variant of super efficiency is implemented such that efficiency scores may be higher than 100 %. When evaluating relative efficiency with DEA, average (industry) efficiency will depend on implementation details like, for instance, the number of evaluated companies (the size of the dataset), the number and specific choice of inputs and outputs, assumptions about scale efficiency, and whether or not super efficiency is modeled. In order to secure efficiency improvements over time and the attractiveness of the industry to investors and employees, it is important that particularly efficient companies can earn more than the normal rate of return. Thus, the efficiency scores are calibrated such that the representative company earns the normal rate of return. We discuss some of these DEA developments in the next section.

Due to the time lag in the use of accounting data, it was argued that new investments must be compensated in order to earn the normal rate of return in a representative company. This was accomplished through a compensation parameter, $CP$ (this parameter and its use is discussed in Bjørndal et al. (2008b). The formula for establishing the revenue of a company in year $t$ could then be written as:

$$Rcap_t = \rho C^{**}_{t-2} + (1-\rho)C_{t-2} + CP = \rho E^*_{t-2} C_{t-2} + (1-\rho)C_{t-2} + CP \qquad (2)$$

where $C_{t-2}$ is the price adjusted cost base from year $t$-2, $E^*_{t-2}$ is the calibrated efficiency score of the company, and $C^{**}_{t-2}$ is the corresponding calibrated cost norm. For the whole industry, the value of the compensation parameter has been calculated to 300-400 mill. NOK. From 2009, the time lags have been removed, so that there is no longer need for the compensation parameter.

[2] Operating and maintenance costs from year $t$-2 were adjusted for inflation, depreciation set equal to the accounting values in year $t$-2, while network losses (NL) were found by taking the losses in MWh in year $t$-2 and multiplying by an average area price (based on Nord Pool Spot) for year $t$. The cost of capital was found by multiplying the book value (BV) of the company assets at 31.12 in year $t$-2 by the NVE rate of return, $r_{NVE}$, for year $t$. This regulated rate of return is determined annually, based on a risk free rate of return and a risk premium. Finally, total cost includes the value of lost load (VOLL) which is calculated as lost load times a unit price, with different unit prices for various customer groups.

# 3 Benchmarking and productivity measurement for regulation

In order to establish reasonable revenue caps for network companies under incentive regulation, it is necessary to analyze company performance. We distinguish between analysis of productivity (absolute performance) and efficiency (relative performance), and most of the analyses performed for regulation purposes belong to the latter category. The two most widely used methods for efficiency analysis are Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). The former method belongs to the group of so-called parametric methods, where one assumes a general mathematical function for the relationship between inputs and outputs, and estimates its parameters. On the other hand, DEA takes a non-parametric approach whereby the efficient frontier is fitted directly to the data. Hence, under DEA there is no need to assume a particular mathematical structure, although one still has to make choices with respect to the assumptions that define the set of feasible production plans and the efficient frontier. There are also alternatives to SFA and DEA, such as Corrected Ordinary Least Square method (COLS)[3], and Stochastic Data Envelopment Analysis (SDEA). An introduction to different benchmarking methods is given by Coelli et al. (2005).

The Norwegian regulator has mainly used DEA for its efficiency analyses. In this section we give a brief introduction to DEA and discuss some important implementation issues related to the Norwegian regulation regime.

## *3.1 Introduction to DEA*

Figure 2 illustrates the computation of technical efficiency under DEA. It shows an example with one product ($y$) and one input factor ($x$), and with five companies A-E. The figure illustrates some of the basic assumptions that are commonly used in DEA and that defines the set of feasible production plans and the efficient frontier. First, note that all DEA models assume that the observed data belongs to the production possibility area, i.e., that they correspond to feasible production plans. It is also common to assume that "synthetic" companies can be constructed by taking convex combinations of the existing data points, as illustrated by the area ABCE in the figure. With production possibility area ABCE, the efficient frontier consists of line segments ABC, i.e., input / output combinations such that output cannot be increased without also increasing input. Another common assumption is that of free disposability, i.e. that surplus quantities of input and output can be disposed of without cost. The latter assumption implies that if $(x,y)$ is a feasible production plan, then $(x',y')$ will also be feasible if $x' \geq x$ and

[3] COLS estimates model parameters using OLS and shifts the intercept of the regression line such that it passes through the minimum observation (Lowry and Getachew, 2009).

$y' \leq y$. This gives the extension of the production possibility area indicated by horizontal lines in Figure 2. Convexity and free disposability give rise to the so-called Variable Returns to Scale (VRS) technology, with a corresponding efficient frontier given by A'ABCC' in Figure 2.

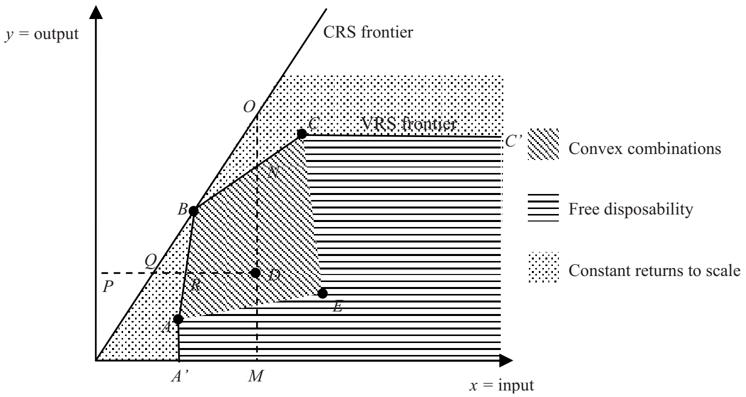



**Figure 2.** Technical efficiency under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS).

Once we have determined the efficient frontier, the efficiency of a particular company can be evaluated by comparing the corresponding data point to a reference point on the frontier. Suppose we wish to evaluate company D and that we are willing to accept the VRS frontier as the correct one. Note that we have an infinite number of reference points to choose from, since it is not obvious in which direction we should move from point D to the VRS frontier. Figure 2 illustrates two typical choices with respect to direction, namely the horizontal (input) and vertical (output) direction. If we choose the input direction, as in the DEA models used for the Norwegian network companies, the reference point for company D will be point R, and the efficiency score can be computed as the ratio PR/PD. On the other hand, if the output direction is chosen, the efficiency score of company D is given by the ratio MN/MD. The input efficiency score PR/PD indicates the potential for reduction in input usage by company D, while the output efficiency score focuses on the potential for increasing output.

In some settings it is also reasonable to assume that any feasible production plan can be freely scaled up or down; i.e., if $(x,y)$ belongs to the production possibility set, this is true also for $(tx,ty)$, where $t$ is a non-negative constant. This extends the production possibility area by the dotted area in the figure. The resulting production technology is commonly referred to as a Constant Returns to Scale (CRS) technology. The CRS efficient frontier is the straight solid line going through the origin in Figure 2, and the efficiency score of company D can be computed as the ratio PQ/PD or MO/MD, depending on which direction one chooses towards the CRS frontier. Note that, since the frontier is a straight line that passes through the origin, we will have PQ/PD = MD/MO; hence the input efficiency score can be found as the inverse of the output efficiency score. This illustrates a general property of CRS models, i.e., that it does not matter whether we choose the input or output direction when we evaluate the efficiency of a company. We also note that the CRS frontier lies further away from the observed data points than the VRS frontier, with the exception of the tangency point B. Therefore, CRS input (output) efficiency scores will always be lower (higher) than, or equal to, the corresponding VRS scores.

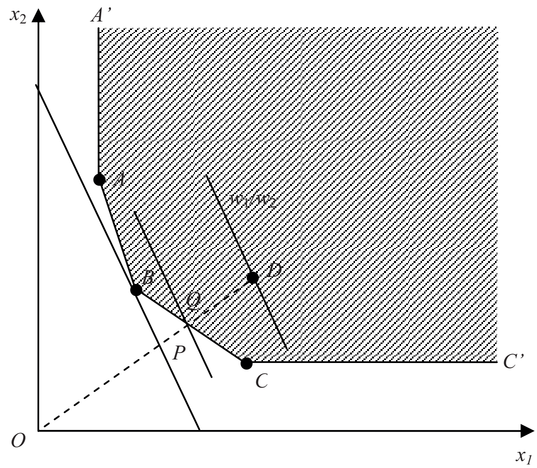



**Figure 3**. Technical efficiency and cost efficiency.

The technical efficiency measure discussed above evaluates the potential for input (output) reduction (increase). In the models that have been used by NVE, input use is measured in terms of cost. DEA cost efficiency models not only measure the potential for reduction in input usage, but also the potential for cost reductions through reallocation between input factors. An illustration of how this can be measured is given in Figure 3. In this example four companies produce the same quantity of output, using two inputs , $x_1$ and $x_2$. Company D is faced with the factor prices $w_1$ and $w_2$, determining the slope of its isocost line. The optimal plan for company D would thus be to choose the same input mix as company B, and the overall cost efficiency of D can be expressed as *OP/OD*. Technical efficiency measures the distance from point *D* to the efficient frontier A'ABCC', i.e. the ratio *OQ/OD*. Allocative efficiency measures the additional cost reduction by improving the input mix at given prices, and can be expressed as *OP/OQ*. The overall cost efficiency can thus be decomposed into technical and allocative efficiency in the following way:

$$\frac{OP}{OD} = \frac{OP}{OQ} \cdot \frac{OQ}{OD}$$

In other words, overall cost efficiency is equal to the product of allocative and technical efficiency. For a more comprehensive introduction to the DEA methodology, see Cooper et al. (2007).

### *3.2 Model specification and data measurement issues*

Equations (3)-(7) below describe a DEA cost efficiency model. The variable $x_{ij}$ represents company *j*'s use of input-factor *i*, $i = 1,\ldots, m$, while $y_{rj}$ represents company *j*'s production of output *r*, $r = 1,\ldots, s$. In order to evaluate the cost efficiency of a particular company *j,* we use the factor price $w_{ij}$ observed by that company for each input *i* that the company uses. The index $j_0$ represents the company that we want to evaluate. The decision variable $z_i$ represents the optimal use of input *i* for the evaluated company. Hence, the objective function (3) measures the ratio between the optimal cost (cost norm) of the evaluated company, and its actual cost. The optimal cost corresponds to a set of peers, and the decision variable $\lambda_j$ measures the weight of company *j* in this reference set. Equation set (4) requires the optimal input quantities of the reference company to be no greater than the optimal input quantities of the evaluated company, and equation set (5) requires the output quantities of the reference company to be at least as great as the corresponding quantities for the evaluated company. Equation (6) enforces the VRS restriction, while (7) ensures non-negative weights of the reference companies.

$$\min_{\lambda,z} \frac{\sum_i w_{ij_0} z_i}{\sum_i w_{ij_0} x_{ij_0}} \tag{3}$$

subject to

$$z_i \geq \sum_j \lambda_j x_{ij} \qquad i = 1,\ldots, m \tag{4}$$

$$y_{rj_0} \leq \sum_j \lambda_j y_{rj} \qquad r = 1,\ldots, s \tag{5}$$

$$\sum_j \lambda_j = 1 \tag{6}$$

$$\lambda_j \geq 0 \qquad j = 1,\ldots, n \tag{7}$$

If we can assume that all the inputs have strictly positive factor prices, we can replace (4) by an equality, and substitute the expression for $z_i$ in the objective function; i.e., we can replace (3) and (4) by the following objective function:

$$\underset{\lambda}{\text{Min}} \frac{\sum_i w_{ij_0} \sum_j \lambda_j x_{ij}}{\sum_i w_{ij_0} x_{ij_0}} \tag{8}$$

The input-oriented VRS model given by (3)-(7), or equivalently, (5)-(8), was used in the regulation of the Norwegian network companies from 1997 to 2006. In the new regulation regime that was implemented from 2007, two important changes were made to the underlying DEA model. The CRS assumption, illustrated in Figure 2, was introduced. Mathematically, this is equivalent to dropping restriction (6) in the LP-problem. In addition, the regulator decided to go from a model with five input factors, with corresponding factor prices, to a model with only one input, namely total cost, with a factor price equal to one. Mathematically, these two changes result in the following model:

$$\underset{\lambda}{\text{Min}} \frac{\sum_j \lambda_j x_j}{x_{j_0}} \tag{9}$$

subject to

$$y_{rj_0} \leq \sum_j \lambda_j y_{rj} \qquad r = 1,\ldots,s \tag{10}$$

$$\lambda_j \geq 0 \qquad j = 1,\ldots,n \tag{11}$$

where $x_j$ is the total cost of company $j$. The numerator in (9) thus gives the value of the optimal cost norm of the evaluated company $j_0$, while the denominator is the actual cost of the company. Note that since the denominator is a constant, the optimal solution with respect to the $\lambda$'s will not change if we replace (9) by the following expression:

$$\underset{\lambda}{\text{Min}} \sum_j \lambda_j x_j \tag{12}$$

By using (12) we obtain the cost norm for the evaluated company directly as the value of the objective function. The shadow prices of the output restrictions (10) will now be expressed in monetary units, making them easier to interpret.

The shadow prices can also be obtained by solving the dual to (10)-(12), given by:

$$\underset{p}{\text{Max}} \sum_r p_r y_{rj_0} \tag{13}$$

subject to

$$\sum_r y_{rj} p_r \leq x_j \qquad j = 1,\ldots,n \tag{14}$$

$$p_r \geq 0 \qquad\qquad r = 1,\ldots,s \qquad\qquad (15)$$

where $p_r$ is the price of output $r$. The dual LP-problem has an interesting interpretation, in which company $j_0$ optimizes non-negative prices for its outputs such that the resulting revenue, given by the value of (12), is maximized. The choice of prices is, however, restricted by (14), saying that no company, including company $j_0$, can have positive profit when evaluated at these output prices.

In the rest of this section we discuss data and model specification issues with respect to the DEA models that have been used as part of the Norwegian regulatory regime since 1997.

### 3.2.1 The number of input factors

Since the outputs of an electricity network company are mostly outside of the company's control, it makes sense to use an input-oriented DEA model with cost as input(s), and where the output factors are assumed to be exogenously given. The input factors that have been used are shown in Table 1.

The models in regulation periods I and II had the same input set, except that a quality cost variable (value of lost load) was added in regulation period II, increasing the number of inputs from four to five. In period I and II there were two versions with respect to capital costs, one based on reported book values and the other based on a catalogue of standard values. Separate DEA analyses were performed for each of the capital definitions, and the final efficiency score for a company was set equal to the maximum of the two efficiency scores.

From period III it was decided to switch to a model with only one input, i.e. as given by (9)-(11), and to use only book values as basis for evaluating capital costs. The five elements that constitute total cost are shown in Table 1. In the rest of this section we discuss the former change, while capital costs is the subject of the next section.

| **Variable** | **Period** | | | **Unit of measurement** | **Factor price** |
|---|---|---|---|---|---|
| | **I** | **II** | **III** | | |
| Labor | x | x | x | No. of man-years | Company-specific average wage |
| Capital, book values | x | x | x | NOK | Depreciation factor + $r_{NVE}$ |
| Capital, catalogue values | x | x | | NOK | Annuity factor based on $r_{NVE}$ and observed asset lifetimes |
| Goods & services | x | x | x | NOK | 1 |
| Power losses | x | x | x | MWh | Based on the system price of power from Nord Pool Spot |
| Value of lost load (VOLL) | | x | x | NOK | 1 |

**Table 1.** Input factors in the various DEA models.

It is easy to show that if two input factors $i$ and $k$ have identical factor prices, i.e., if $w_{ij} = w_{kj}$ for all companies, then we can replace them by a single input $l$, defined as $x_{lj} = x_{ij} + x_{kj}$, without changing the efficiency score given by the value of (8). Table 1 shows that this applies to goods & services and VOLL. In the case of power losses there was a common factor price for all companies, given by the average system price. By rescaling the quantities and prices for this input factor, we can change the factor price of losses to unity without altering the value of (8). Hence, it would have been possible to reduce the number of inputs in regulation period II from five to three without changing the results.

For the remaining two inputs, labor and capital, there was considerable variation among the companies. Figure 4 shows the distribution of the wage numbers in the dataset for period II. Since a company's factor price for labor is the *average* wage for its employees, we would expect to see moderate variations among the companies. The large variations that we see in the figure suggest the existence of reporting errors, see the discussion in Bjørndal et al. (2004).

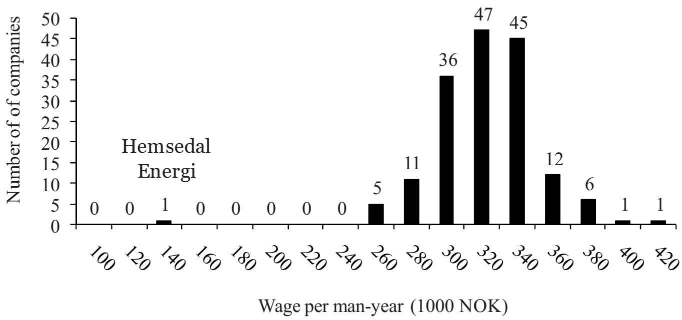
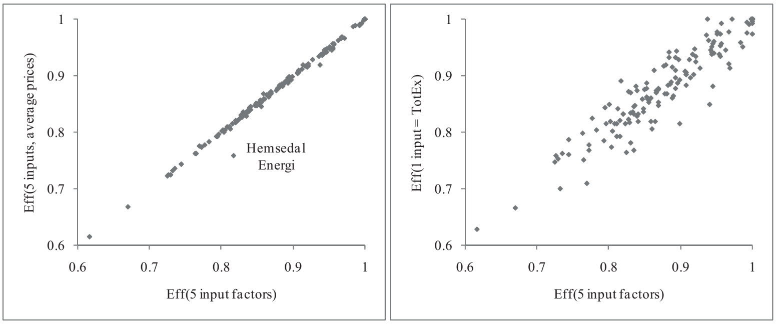



**Figure 4**. Wage factor prices in the distribution network dataset for 1996-1999.

Figure 5(a) illustrates the effect of variation in the factor prices. We have replaced the individual factor prices with, for each input factor, a weighted average over all the companies; i.e., we measure efficiency assuming all companies have access to the same input factor market with a common factor price. We see that the effect of this operation is quite small, except for one company, corresponding to the outlier in Figure 4.




(a) (b)

**Figure 5.** Effect of (a) using average instead of individual factor prices and (b) replacing the 5 inputs with a single input factor (TotEx), 1996-1999 dataset.

It is tempting to conclude from the analysis in Figure 5(a) that, since measuring efficiency with company-specific factor prices gives almost the same results as when using a common factor price, it should be possible to get rid of the remaining two input factors as well, with very small changes in the efficiency results. This is, however, not correct, as illustrated by Figure 5(b) where we compare the results from model (5)-(8) and model (9)-(11), with five and one input(s), respectively. In order to understand this apparent puzzle, note that rescaling the labor and capital factor prices so that they are equal to unity for all companies also requires rescaling of the corresponding factor *quantities*. As it turns out, changes in factor prices and factor quantities can have very different effects on individual efficiency scores, even if they result in the same change in total cost. This is illustrated by the example in Table 2, which refers to a company with initial labor expenses of 29.3 MNOK and an efficiency score of 87.96 %. Case I shows what would happen if labor expenses were reduced to 4.7 MNOK. If this is done via a reduction in the factor price, i.e., from 311 112 NOK to 50 000 NOK, the efficiency score would increase by 2.67 %. The same cost reduction could be obtained by reducing the number of man-years from 94.05 to 15.12, as shown in the table. In this case, however, we see a much larger increase in the efficiency score, by 12.04 %. Case II and III further illustrates that changes in factor quantities have a much stronger effect on efficiency scores than equivalent changes in factor prices.

| Case | Number of man-years | Wage per man-year | Total wage expenses | Efficiency score | Change |
|---|---|---|---|---|---|
| Initial | 94.05 | 311 112 | 29 260 084 | 87.96 % | |
| I | 94.05 | 50 000 | 4 702 500 | 90.63 % | 2.67 % |
| | 15.12 | 311 112 | | 100.00 % | 12.04 % |
| II | 94.05 | 250 000 | 23 512 500 | 88.59 % | 0.63 % |
| | 75.58 | 311 112 | | 91.02 % | 3.06 % |
| III | 94.05 | 500 000 | 47 025 000 | 86.25 % | -1.71 % |
| | 151.15 | 311 112 | | 79.58 % | -8.38 % |

**Table 2.** Quantity versus price effects in the case of labor expenses.

More details about these examples can be found in Bjørndal et al. (2004). For a general treatment of the choice of input factors, see Dyson et al. (2001). There is also some literature on input aggregation, see e.g. Tauer (2001) and Färe et al. (2004).

### 3.2.2 Capital costs and age effects

The electricity network industry can be characterized as capital intensive, with large investments in equipment with long asset lifetimes. Therefore, the quality of the efficiency analyses depends heavily on the way capital costs are measured. Alternative methods for calculating capital costs exist, and in practice the choice is often between methods based on linear depreciation or annuity-based methods. In the first two regulation periods in Norway, both of these models were used side by side, as shown in Table 1. In the third regulation period only one method, with linear depreciation based on book values, is used.

From industry representatives it is often claimed that equipment productivity is nearly constant throughout the life span of the equipment, which suggests the use of annuity-based methods. In fact, using book values and linear depreciation may lead to a negative bias in the efficiency scores, as illustrated by the stylized example in Figure 6. Here we have created a dataset with 30 companies, where the only difference between the companies is their age. The companies are assumed to have two types of costs, capital costs and operating costs[4]. The figure illustrates that efficiency analysis with annuity-based capital costs yields efficiency scores that are independent of age, whereas efficiency scores based on linear depreciation will be increasing with respect to age. In the latter case the efficiency scores will also depend on whether we use model (5)-(8) with two inputs or model (9)-(11)

[4] The interest rate is 5 %, and the operating costs have been set equal to the annuity-based capital costs.

16

with total cost as the single input, since factor prices in this case will differ among companies[5].

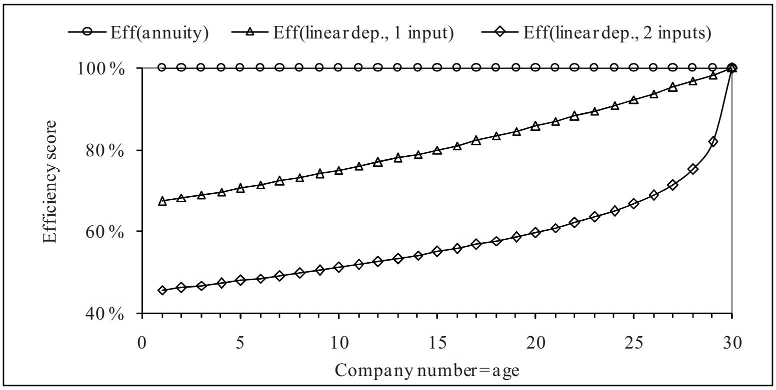



**Figure 6**. Efficiency scores for an industry consisting of 30 vintages of a representative company.

Looking at the dataset that was used in the second regulation period, we find some evidence of age bias, as illustrated by Figure 7. The diagram shows that efficiency scores are significantly lower for "young" companies, i.e., where the ratio between book value and catalogue value (new value) is relatively high.

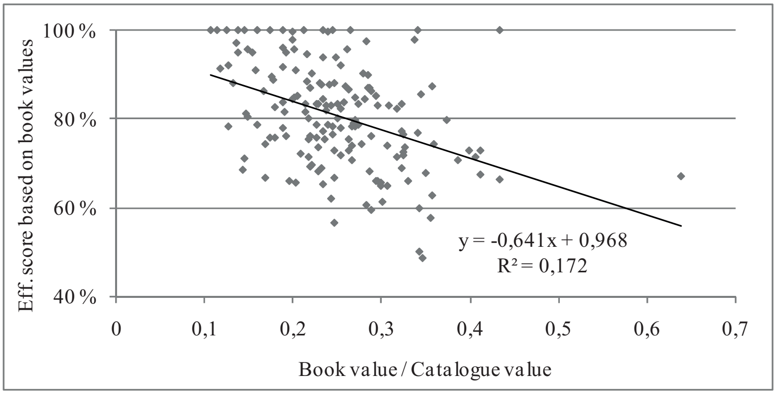



**Figure 7.** Efficiency scores versus age in the 1996-1999 dataset for distribution companies.

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[5] In the cost efficiency model used in the first two regulation periods, the factor price for capital in the book value model was set equal to the sum of the depreciation rate and the interest rate, where the depreciation rate was calculated as depreciation divided by book value. Since book values decrease with age, and depreciation is constant, factor prices will differ due to age.

The efficiency analyses are used to compute the cost norms for the regulation model; hence a bias in the efficiency scores may influence the revenue caps. In Figure 8 we illustrate this phenomenon, using the same example as in Figure 6. We assume that the companies last for 30 years, and that one company is added to / removed from the dataset each year. Apart from the ages of the existing companies, there are no changes to the industry over time. The diagram illustrates the development in cost and cost norm for a company during its 30-year life span. The dashed and dotted lines in the figure show calculated costs based on linear depreciation and annuities, respectively. We assume that the revenues are set equal to the cost norms; hence the dashed and dotted lines correspond to revenue caps under a rate of return regulation regime. Both of these alternatives have a profitability (IRR shown in parentheses) equal to the cost of capital. If, however, we let the revenue caps be determined by a cost norm based on DEA analysis with book values, the revenue level will be set equal to the cost of the oldest company in the dataset, i.e., a 30-year old company. If the age bias is not compensated for, the resulting profitability will be only 0.3 %.

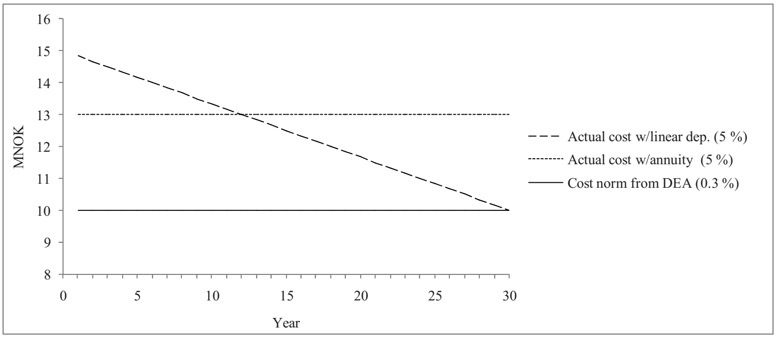


**Figure 8.** Actual costs and cost norms over the life span of a company.

The obvious way to correct the age bias would be to define the capital costs to be constant over time, e.g., by using annuities and catalogue values. If this is not viable, e.g., due to lack of data, there are several alternatives. One alternative is to introduce an age parameter as an extra output parameter in order to correct the bias. Alternatively, one could correct the bias by adjusting the efficiency scores / cost norms *after* running the DEA analysis. Such a calibration of the efficiency scores could be implemented for a number of reasons, not only age bias, and will be discussed in one of the sections below. Both alternatives are discussed in detail by Bjørndal & Bjørndal (2006a/b) and Bjørndal et al. (2008b). The use of an age parameter is related to the discussion of *environmental* variables in e.g. Dyson et al. (2001).

### 3.2.3 Choice of output variables

We can distinguish between output variables that describe characteristics of the companies themselves versus variables that serve to describe the environment in which the companies operate. Some of the variables that are listed in Table 3 and Table 4 below clearly belong to the first category, such as delivered energy and the number of customers, while others, such as forest, snow and coast, belong to the latter. Network size variables such as HV and LV lines cannot be easily classified as either "pure output" or "environmental" variables. The motivation behind their inclusion is to represent demographical and topological factors that influence the companies' network size and cost level, and it is lack of available data that has made it necessary to represent these factors using input variables as proxies.

Note that some of the environmental factors are represented by indices. For instance, the forest index is given as a percentage value, measuring how much of a concession area is covered by high-growth forest. Indices must be correctly scaled before used together with scale-dependent variables in a DEA model, otherwise the results will be biased in favor of small companies[6].

| Variable | Unit of measurement | Regulation period | | |
|---|---|---|---|---|
| | | I | II | III |
| Delivered energy | MWh | x | x | x |
| Customers | No. of customers | x | x | |
| Customers, except cottages | No. of customers | | | x |
| Customers, cottages | No. of customers | | | x |
| HV lines | Kilometers | x | x | x |
| LV lines | Kilometers | x | x | |
| Sea cables | Kilometers | x | | |
| Expected VOLL | NOK | | x | |
| Network stations | No. of stations | | | x |
| Interface | Weighted measure | | | x |
| Forest | Forest index × HV overhead lines | | | x |
| Snow | Snow index × HV overhead lines | | | x |
| Coast | Coast index × HV overhead lines | | | x |

**Table 3.** Output variables for distribution networks.

[6] See Dyson et al. (2001).

| Variable | Unit of measurement | Regulation period | | |
|---|---|---|---|---|
| | | I | II | III |
| Transported effect | MW | x | x | |
| Network size | Weighted value | x | x | |
| Exchange | Weighted value | x | x | |
| Central grid tasks | Weighted value | x | x | |
| Expected VOLL | NOK | | x | |
| Lines, air | Weighted value | | | x |
| Lines, earth | Weighted value | | | x |
| Lines, sea | Weighted value | | | x |
| Interface | Weighted value | | | x |
| Forest | Forest index × Overhead lines | | | x |

**Table 4.** Output variables for regional transmission networks.

Note that, because of the output restrictions given by (5), adding a new variable to the output set will have a non-negative effect on the efficiency scores. An example is shown in Figure 9, which illustrates the effect of adding the so-called "geography" variables to the DEA model for distribution networks in regulation period III. We see that the new variables cause an increase in the average efficiency score from 87 % to 90 %. Since the maximum obtainable efficiency score is 100 % and the number of efficient companies can only increase when we add variables, the dispersion of the efficiency scores will inevitably decrease. This is a well-known problem, i.e., that adding more variables will reduce the discriminatory power of the DEA model, and one should therefore try to restrict the number of variables relative to the number of companies in the dataset. As a rule of thumb, Dyson et al. (2001), for instance, recommend that the number of companies should be at least $2m{\times}s$, where $m$ and $s$ are the number of input and output variables, respectively.

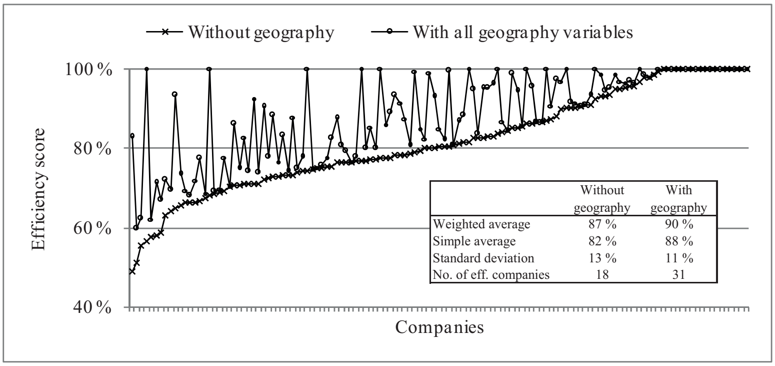


**Figure 9.** Effect of adding geography variables (forest, snow, coast), 2006 dataset.

In order to evaluate potential variables for inclusion in the output set, there exists statistical tests, see Banker & Natarajan (2004). Such tests have been used in the development of the various DEA models that are discussed here, see Kittelsen (1993) and NVE (2006a). In order to illustrate some implications of the testing procedures, we use an example of a test that was done in connection with the development of the third regulation model. Table 5 shows four different T-tests that tests whether the mean efficiency score increases significantly (with a 5 % significance level) as a result of adding either HV or LV as a new output variable[7]. We see that both variables have a significant effect if they are added to an output set consisting of the customer and energy variables. However, if the LV variable is added to an output set already containing the HV variable, it does not have a significant effect. The opposite is not true, i.e., the HV variable has a significant effect even though the LV variable is already in the output set. The example shows that the outcome of the test procedures may indeed depend on the sequence in which the variables are tested. In NVE (2006a), the HV variable was included in the output set from the start, i.e., it was never tested, and the conclusion was therefore that the effect of the LV variable was not significant. The regulator used this, combined with suspected low data quality, as an argument for dropping the variable. The regulator's decision was criticized[8], and the main counter-argument was that HV and LV are both endogenous variables. By including one of them, while at the same time excluding the other, we will distort the investment incentives of the companies. It could therefore be argued that the LV variable should be included in the output set even though it does not pass the statistical test.

| New variable | Already included variables | | | | t | p(T > t) |
|---|---|---|---|---|---|---|
| | Cust. | Energy | HV | LV | | |
| HV | x | x | | | 17.3 | 0.00 |
| LV | x | x | | | 8.7 | 0.00 |
| HV | x | x | | x | 9.4 | 0.00 |
| LV | x | x | x | | 1.4 | 0.08 |

**Table 5.** Test statistics for HV-lines and LV-lines, pooled dataset for 2001-2004.

### 3.2.4 Scale assumption

Assumptions with respect to economies of scale can have a significant effect on the efficiency evaluation of individual companies, as illustrated by Figure 2, where we see that the CRS frontier results in a much stricter evaluation of small and large companies than the VRS frontier. The VRS restriction (6), combined with the output restriction (5), implies that for VRS models a company that is largest with respect to an output is automatically 100 % efficient, since it must be

[7] The formulas can be found in Kittelsen (1993).

[8] See NVE (2006b).

its own reference. To illustrate the consequences of this property for the regulation, we show in Table 6 the largest companies with respect to output parameters in the distribution dataset from regulation period II. Since there were four companies that were evaluated as 100 % efficient irrespective of their cost level, we claim that a large share of the industry, representing some 600 000 out of 2.5 million customers, was rather weakly regulated. In fact, the weak regulation of large companies with VRS models was stated as one of the main reasons for switching to a CRS model in regulation period III, see NVE (2006a). The DEA literature also proposes statistical tests for determining the appropriate assumptions with respect to economies of scale, see Banker (2004).

| Output | No. of units | Company | No. of customers |
|---|---|---|---|
| Low voltage lines (km) | 8 951 | BKK Distribusjon AS | 147 500 |
| High voltage lines (km) | 4 969 | Nord-Trøndelag El.nett | 73 557 |
| Customers | 303 312 | Viken Energinett AS | 303 312 |
| Delivered energy (MWh) | 8 370 400 | Viken Energinett AS | 303 312 |
| Exp. cost of non-delivered energy (1000 NOK) | 48 089 | Troms Kraft Nett AS | 59 376 |

**Table 6.** The largest company with respect to each output factor, 1996-1999 dataset.

### 3.2.5 Super efficiency and incentives

A regulation scheme should give the regulated companies strong incentives for cost efficient investment and operating decisions. This implies that a company's cost norm should be independent of its actual cost. This is especially apparent in the yardstick regulation regime that was introduced in 2007, where a new cost norm is established each year via the efficiency analyses. When a company reduces its cost level, this should not lead to a reduction in the cost norm, since that would give the company weaker incentives for cost reductions (the . This property is not fulfilled for a 100 % efficient company, however, since the cost norm for such a company will be set equal to its actual cost.

One way to avoid this phenomenon is to apply the procedure suggested by Andersen & Petersen (1993), whereby the evaluated company is excluded from the dataset. We see an example of this in Figure 10. The revised efficiency scores are only different for those companies that would otherwise have an efficiency score of 100 %. Some companies would get very high efficiency scores if this procedure was to be used, and the regulator chose a modified procedure, as described in NVE (2006a). According to the revised procedure, super efficient companies are re-evaluated against a dataset from the year(s) preceding the year of the current dataset. The DEA model in the second step includes data for the company itself;

hence a company can only appear as super efficient if it has improved its performance relative to the previous year(s)[9].

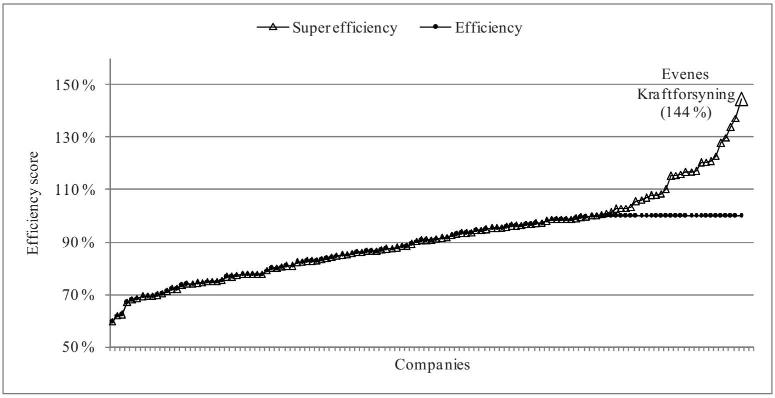


**Figure 10.** Ordinary efficiency and super efficiency scores, 2006 data for distribution companies.

Table 7 illustrates the incentive effects of the different models with respect to super efficiency, given a yardstick regulation model as in (1), with $\rho = 0.6$. Suppose a company with an efficiency score of 100 % is considering an investment decision that will result in a permanent reduction in the annual cost of 10 MNOK. If the DEA model does not consider super efficiency at all (Model 1), the cost norm of the company will be set equal to its actual cost; hence the reduction in the revenue cap will be equal to the cost reduction, and the company will have no incentives to reduce its cost level. Model 2 measures super efficiency á la Andersen & Petersen (1993); hence the cost norm will be unaffected by the change in the actual cost level. With this model, therefore, the company will experience a permanent increase in its profit equal to 60 % of the cost reduction. Model 3 corresponds to the "restricted" super efficiency measure that is used by the regulator, where the company's efficiency is re-evaluated against a dataset containing its own cost and output data for the previous year. In the first year the cost norm will be set equal to the company's cost for the previous year; hence there will be no reduction in the cost norm, and the profit for that year will be the same as with Model 1. From the second year and onward, the cost norm will catch up with the actual cost level, and the effect on profits will be zero. Although this example is somewhat simpli-

[9] For 2007, the initial DEA analyses were based on data from 2005, and the re-evaluation in the second step was against a dataset from 2004. For 2008 and 2009, the re-evaluation dataset was created by taking averages of the datasets for the periods 2004-2005 and 2004-2006, respectively.

fied[10], it clearly illustrates that a model where little or no super efficiency is allowed will provide relatively weak incentives for cost reductions.

| | **Model \ Year *(t)*** | **20x1** | **20x2** | **20x3** |
|---|---|---|---|---|
| $\Delta C_t$ | | -10 | -10 | -10 |
| | 1 | -10 | -10 | -10 |
| $\Delta C^*_t$ | 2 | 0 | 0 | 0 |
| | 3 | 0 | -10 | -10 |
| | 1 | -10 | -10 | -10 |
| $\Delta Rcap_t$ | 2 | -4 | -4 | -4 |
| | 3 | -4 | -10 | -10 |
| | **1** | **0** | **0** | **0** |
| $\boldsymbol{\Delta \Pi_t}$ | **2** | **+6** | **+6** | **+6** |
| | **3** | **+6** | **0** | **0** |

**Table 7.** Incentive effects of DEA models with (1) no super efficiency, (2) unrestricted super efficiency, or (3) restricted super efficiency á la NVE**.**

### 3.2.6 Calibration and average profitability

The discussion of super efficiency in the previous section shows that the *marginal* incentives in the industry depend on the specification of the benchmarking model. However, model specification also influences the *average* profitability of investments / companies, as illustrated by Table 8 below, where we show average and cost weighted average efficiency for various versions of the DEA model (scale assumption, super efficiency). From the cost weighted average efficiency score we can also compute the total cost norm for the whole industry. In the present yardstick model, only companies with an efficiency score of at least 100 % will be able to earn the NVE rate of return. Since the NVE rate of return is determined as the sum of the risk free rate and a suitable risk premium estimated using CAPM, it is reasonable that some companies, if they manage to run their business in an efficient manner, should be able to earn *more* than the NVE rate of return. This may be achieved to some extent by introducing super efficiency in the model. However, as can be seen from Table 8, the industry cost norm will be only 91 % of the actual industry cost if super efficiency is introduced, compared to 88 % for the comparable CRS model without super efficiency.

[10] Time lags are not considered. Also, the regulator has gradually increased the number of years that the dataset in the second step is based on, cf. footnote 9.

| | VRS | CRS | CRS w/super efficiency | Modified super efficiency (NVE) |
|---|---|---|---|---|
| Simple average | 88 % | 85 % | 88 % | 85 % |
| Cost weighted average | 93 % | 88 % | 91 % | 89 % |
| Industry cost norm (MNOK) | 9168 | 8666 | 8948 | 8709 |

**Table 8.** Industry average of the efficiency scores for various DEA models. Distribution networks, 1996-1999 dataset.

This raises an interesting question, namely, how much of the total cost should the industry as a whole be allowed to collect in the form of revenues? It does not seem fair that the total revenue level of the industry should be determined by somewhat arbitrary model specification choices, as illustrated by Table 8. In the first two regulation periods, the initial revenue level was set equal to the companies' actual costs, with subsequent reductions given by general and individual efficiency requirements. For the third regulation period, the regulator decided to calibrate the cost norms such that the industry revenue would be set equal to the sum of actual costs for the industry[11].

There are, of course, a number of ways by which the initial revenue shortfall could be distributed among the companies, and the following three methods have been used by the regulator so far in regulation period III:

(A) To normalize the efficiency scores such that the cost weighted average becomes equal to 100 %. This is equivalent to distributing the revenue shortfall in proportion to the initial cost norms of the companies[12].

(B) To distribute the revenue shortfall among the companies in proportion to their capital values.

(C) To add a constant to the efficiency score of each company, such that the cost weighted average becomes equal to 100 %. This is equivalent to distributing the revenue shortfall in proportion to the actual costs of the companies[12].

The methods differ with respect to the effect on *marginal* incentives and *average* profitability. To see the difference in marginal incentives, note that the basis for distributing the revenue shortfall is different. Actual capital and cost values depend on decisions taken by the companies, while cost norms, at least in principle, cannot be influenced by the companies' own decisions. This gives method A an advantage over the other two methods as far as incentives are concerned. The differences with respect to average profitability follows from the different cash flow time profiles, as illustrated by Figure 11 for the same example that we used in Figure 8. The lines marked with circles, squares and triangles correspond to calibrated cost norm profiles for the respective calibration methods. Method A represents a vertical shift in the cost norm curve, but since the new cost norm is lower than the annuity-based cost for every year, the new profitability will be low-

[11] See NVE (2006a).

[12] See Bjørndal et al. (2008).

er than the cost of capital. Method B tilts the cost norm curve such that is it almost equal to the cost based on book values, and this yields a higher profitability than for method B, although still slightly lower than the cost of capital. Method C is similar to method A, but here we see both a vertical shift *and* some tilting of the cost norm curve. Profitability is still lower than the cost of capital.

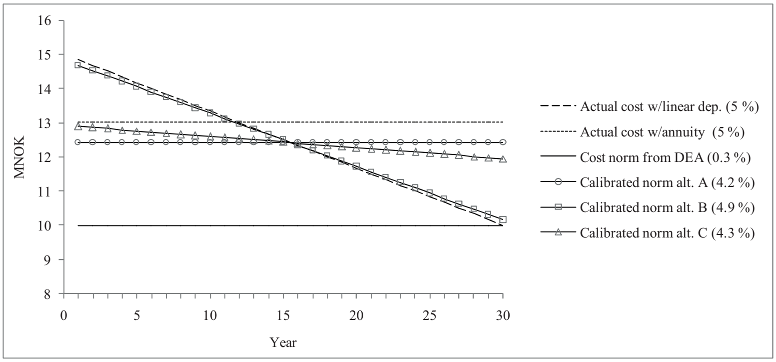


**Figure 11.** Cost norms over the life span of a company, with and without calibration.

Table 9 shows the magnitude of the calibration effects on ex ante revenue caps for the industry in 2007 and 2008. For these two years, the regulated rates of return were 8.09 % and 8.38 %. The calculation of the revenue caps were made in three steps. In Step 1 some minor adjustments, related to the VOLL cost element, were made to the efficiency scores. In Step 2, the efficiency scores were adjusted to bring the industry average up to 100 %[13]. In Step 3 the revenue caps were adjusted in order to compensate for the reporting time lags in the regulation model[12], and then a final calibration was performed in order to bring the industry revenue level (down) to the actual cost level for the industry. We see that the two adjustments in Step 3 cancel each other out at the industry level, although the net effect can be positive or negative for individual companies[14]. The main calibration effect, therefore, was achieved in Step 2, where the industry revenues were increased by 599 MNOK and 786 MNOK, respectively. Note that the corresponding "profitability" effects of 1.55 % and 2.01 % are somewhat misleading, since the percentages have been calculated with respect to capital reported for year *t-2*; i.e., these are not actual profitability effects. More details on calibration can be found in Bjørndal & Bjørndal (2006b) and Bjørndal et al. (2008b).

[13] In 2007 calibration method A was used in order to achieve this, and in 2008 method C was used.

[14] In total, the companies were not given compensation for time lags, although, as pointed out by Bjørndal et al. (2008b), they should be. As a consequence, reporting time lags have been removed from the regulation since 2009.

| | 2007 | | 2008 | |
|---|---|---|---|---|
| | MNOK | "Profitability" | MNOK | "Profitability" |
| Revenue cap based on DEA eff. scores | 12 986 | 6.54 % | 13 848 | 6.37 % |
| Effect of adjusting eff. scores (step 2) | 599 | 1.55 % | 786 | 2.01 % |
| Revenue cap after step 2 adjustments | 13 585 | 8.09 % | 14 635 | 8.38 % |
| Compensation parameter (step 3) | 328 | 0.85 % | 371 | 0.95 % |
| Rev. cap before calibration (IR1) | 13 913 | 8.94 % | 15 006 | 9.33 % |
| Calibration effect (step 3) | -328 | -0.85 % | -372 | -0.95 % |
| Final revenue cap (IR2) | 13 585 | 8.09 % | 14 634 | 8.38 % |

**Table 9.** Calibration effects for the entire industry in 2007 and 2008.

## 4 Concluding remarks

In this paper we have given an overview of the benchmarking models used in the Norwegian incentive regulation after 1997. We discuss some specific issues as regards to the development of the DEA models. This concerns model specification issues such as the choice of scale assumptions and input and output variables, but also how the results from the benchmarking models are used, i.e. translated into revenue caps. Due to the considerable effects that model specification and data measurement choices can have on efficiency scores (and thus revenue caps), we argue that in order to specify reasonable DEA models, thorough knowledge about the cost structures and cost drivers of the industry is required. Moreover, we show that in order to achieve the goals of the incentive regulation, some adjustment to the benchmarking results may be necessary, before they can be applied in the revenue cap formula.

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# Paper II

# Household Choice of Electricity Retailer

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August 30, 2021

**Abstract**

Despite measures to encourage consumer switch activity through transparent prices and elimination of any switch-related fees, a large percentage of households in Norway, one of the first electricity sectors to undergo liberalization, have not changed electricity retailers. This paper explores influences in households' switch decision by utilizing a survey dataset on households' preferences in electricity related issues. The study adds new insights about consumer behavior and demonstrates that issues related to market design and psychological factors affect households' propensity to switch. In particular, the study identifies that inherited privileges held by former vertical integrated retailers have been disruptive to securing an efficient market and kept a substantial amount of households in their current situation. Hence, we learn that switch numbers seem to relate to particular market characteristics and that there is a complexity relating to various effects in households' switch activity. Thus, findings highlights the importance of looking beyond and bringing in the elaborateness in households' switch decision as to correct for and gather new and more sophisticated insights into potential sources of reluctance to switch. Such that these can be targeted with the most effective policy measures to facilitate an efficient expansion of the retail market in the long run.

**Keywords:** Electricity retail market, switching behavior, Norway
**Submitted to:** Energy Policy (Under review)

## 1 Introduction

Well-informed consumers who make fully controlled choices and choose the "best deal" strengthen competition to the benefit for economic welfare. Thus, lack of consumer participation is one

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source that diminishes the benefits of consumer choice. To pursue a better understanding of household propensity to switch, this study takes into consideration that context matters. And that a wholesome description of the setting where switch decisions are made is essential to establish an understanding of how individuals decide. Hinging on Diamond (2008), this study embraces both economic and psychological factors to be of relevance to influence consumers' actions and preferences in decision making.

There are different approaches to rationalizing friction in consumer mobility taking into consideration that context is of essential importance in influencing choices. A vast and rich collection of empirical studies relate and explain such deviations by investigating contexts relating to psychological factors and market structure issues. Thaler (1980) formalizes this theoretical rationale in his paper "Toward a positive theory of consumer choice" and argues that "an exclusive reliance on normative theory leads economists to make systematic, predictable errors in describing or forecasting consumer choices". In a recent study on consumer switching in retail electricity markets in New Zealand, Ndebele et al. (2019) find that non-price attributes of electricity services are significant determinants to explain the perceived inertia in this market. Deller et al. (2017) identify factors which may impede switching in the UK energy market and conclude that much of the behavior might be understood within the rational choice framework, whereas the whole picture requires an understanding of a wide range of factors. Hereunder are non-price preferences and concerns about the switching process. An additional study taking into consideration the wider context for understanding consumers' switch behavior is that of Barr et al. (2009). This study emphasizes how human behavior is heavily context dependent, and is thus a function of both the person and the situation.

Investigating drivers behind consumer choice and low switch rates in electricity retail markets, is very relevant. Numerous studies address the topic and try to understand the drivers behind consumer choice. However, as stated in Mulder and Willems (2019) "although there are many parallel developments across retail markets, the effectiveness of behavioral and structural regulatory measure depends also on regional and cultural differences and are path dependent". Thus, emphasizing the complexity in understanding consumer choice.

In an attempt to analyze the aftermath and efficiency outcomes of market liberalization in Norway, previous studies by Johnsen (2003), Littlechild (2006), and von der Fehr and Hansen (2010) concluded that the retail segment of the electricity market in Norway functions well when seen from an institutional perspective: (1) electricity prices are readily available for comparision at an official price comparison site, (2) there is a well-established system in place to handle switching, (3) any switching fees were eliminated in 1998. Despite this, von der Fehr and Hansen (2010) emphasize that the picture of consumer switching is nuanced due to a separation of consumers into two distinct groups; active and inactive market participants.

The purpose of this study is to gain insight into potential economic and psychological factors that influence households' switch decision of electricity service provider. Thus, the study builds on a theoretical framework that embraces both psychological factors along with economic influences as plausible factors that may affect consumers' switch decisions. This is in line with similar studies on consumer choice in the Swedish and Danish electricity retail markets (Ek and Söderholm, 2008; Yang, 2014).

The study uses a unique survey dataset on households' attitudes to electricity-related issues, collected for the Norwegian Water Resources and Energy Directorate (NVE) by IPSOS MMI in 2013. The analysis uses probit regression techniques in a binary choice framework and test whether both economic and psychological factors affect the propensity to switch retailers.

In contrast to previous studies on the electricity retail market in Norway, this study goes beyond the observed segmentation of passive and active consumers to explore the factors determining switch decisions and thus provides new empirical insight into households' choice.

Prior to 1999, high costs and the lack of an established system in place to handle switching and metering prevented households from switching, despite the theoretical opportunity that was introduced by the market reform in 1991. Figure 1 shows the development in contract allocation for standardized contracts[1], where the major trend has been switching from the variable price contract to a market price contract. The volume of households preferring a fixed price contract has decreased under the period of this study and remains small in volume. As shown in Figure 2a there was an immediate steep increase in switching from 1998, after elimination of any switch-related fees[2] and the introduction of an official price comparison site. Although there is an increasing trend in the total average percent of households that performs a switch, as shown in Figure 2a, recent numbers from NVE (shown in 2b) show that on average less than 3 out of 10 households perform a switch of retailer each year.

[1] Standardized contracts comprises the variable price contract, the market price contract, and a fixed price product of which contractural terms are defined by the Standard Agreement for Power Supply that came into force in 1996

[2] There are no regulations to this market and retailing takes plays according to the general Consumer Purchases Act.

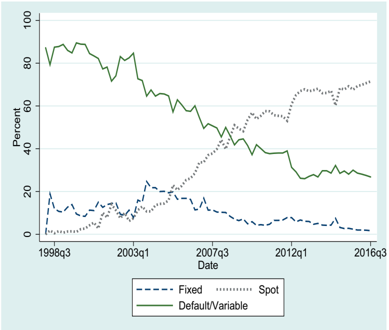
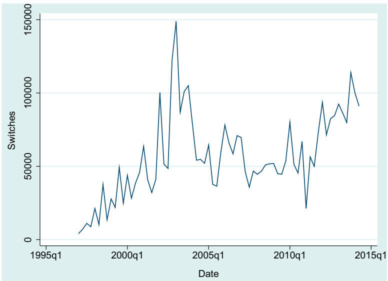
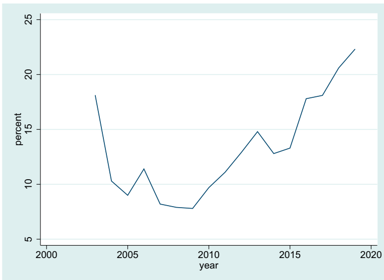



Figure 1: Allocation of standardized contracts over time. Source NVE.

This indicates that although the market matured, as evidenced by increased switch numbers, the majority of households do not take advantage of the opportunity to switch. Thus, there is a significant unrealized welfare improvement to this market.




(a) Number of households switching retailer. Source NVE




(b) Average yearly percent of households that have switched electricity retailer. Source NVE

Figure 2: Switching numbers

The rest of the paper is organized as follows. Section 2 presents the theoretical rationale and methodological basis to support the choice of variables to include in the analyses. Section 3 presents the survey sample. Section 5 presents the switch model, and section 6 provides the conclusion and policy i mplications .

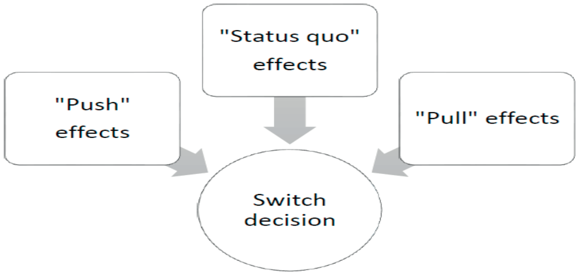



Figure 3: Theoretical framework for analyzing households switch decision of electricity retailer. Source: based on the theoretical framework outlined by Bansal et al. (2005) and the application by Ek and Söderholm (2008) from a study on switching behavior in the Swedish electricity retail market.

## 2 Economic and psychological factors of household switching

While traditional economic benefits are easy to quantify and measure, such as costs saved and the increased utility from saved costs, the non-economic benefits are less straight forward to quantify.

The following review relates both perspectives to pursue a wholesome understanding of the context in which household choices are made. Thus, we treat both psychological and economic factors as relevant influences on households' switch behavior. In line with a similar study on the Swedish electricity retail market by Ek and Söderholm (2008), this study adopts a modified theoretical framework put forth in Bansal et al. (2005) to study households' switch behavior of service providers. As shown in Figure 3 households' switch decision of service provider are driven by three factors: (1) "pull effects"; economic or psychological factors drawing prospective switchers to the alternative supplier induced by a positive association with the alternative service provider, (2) "push effects"; denoted as factors that motivate households to leave an origin induced by negative associations perceived by the current supplier, and (3) from "status quo effects"; that capture the complexity and obstacles in a switch decision, such as switching costs, social norms, and specific attitudes towards switching and past behaviors, so called "mooring" effects. This paper adopts this theoretical framework as a tool to conceptualize the factors that are of potential importance in inducing households' switch choice in this market; either influenced by economic or psychological factors (or both).

A vast and rich literature relate household switching behavior to various "Status-quo" effects. Thaler (1980) analyzes consumer choice from the perspective of a group of economic mental illusions, by linking the psychology involved in a choice to the actual outcome of a decision. Thaler argues that there are certain classes of decisions that are particularly likely to deviate from the predictions of the normative economic model. One known as the endowment effect, in which there is an asymmetry involved in the value of giving something up compared to acquiring the same thing, such that the cost of giving something up is higher. This fits well with the notion that there is a stickiness related to switching to an alternative. The endowment effect causes a bias in favor of the incumbent. The asymmetry that causes the endowment effect can also be described as a "locked-in situation" due to the perception that the disadvantages of giving something up are larger than the gains. Thus, the current situation is triggered by an inherent "status-quo"-effect in favor of the current situation. Defeuilley (2009) links such "status-quo"-effects to loyalty in favor of the incumbent. The study argues that a duality among consumers, meaning that some consumers are loyal to the incumbent and others are not, allows retail suppliers to implement strategies of price discrimination based on geographic location and that sticky consumers remain loyal. Hence, there is an inherent status quo effect driven by loyalty to the current service provider.

Klemperer (1987) explain the significance of the status quo in an attempt to explain consumers' choices and notes that ex ante homogeneous products become heterogeneous after they are purchased. These results support the notion that consumers favor the incumbent firm, and brand loyalty is thus a plausible rationale to explain passive behavior among customers. The findings of Samuelson and Zeckhauser (1988) are in line with Klemperer's findings on consumers' decision making; a series of decision making experiments showed that consumers have a bias toward sticking with the status quo for psychological reasons linked to the certainty of what you have compared to what you may get. The study emphasizes that decision makers exhibit a significant status-quo bias and a preference for the current state. In line with this, Hartman et al. (1991) demonstrated consumers' loyalty through a survey study in which respondents were asked to choose and rank alternative service programs offered by different Californian electricity retailers. The compelling finding from this study is that respondents showed a striking status quo bias toward the current service program offered by their current retailer. Another study which emphasizes the importance of loyalty as a status quo effect is a study by Gärling et al. (2008). This study investigates attitudes towards switching supplier in different liberalized markets[3], and concludes that loyalty to the incumbent, difficulty in information searching, and perceived lack of economic benefits from switching are of primary importance. Gamble et al. (2009) elaborate the loyalty finding of Gärling et al. (2008) and suggest loyalty to be highly significant in determining switch behavior in a fictitious Swedish electricity retail market.

A more recent study by Hortaçsu et al. (2017), focusing on the Texas retail electricity market, adds support to previous findings on a brand advantage attached to the incumbent retailer. Hence, that (related to our theoretical framework), any positive or negative associations with an alternative service provider are equaled out by the incumbents brand advantage, preventing households from switching to a better deal.

While it is clear that the incumbent advantage is a relevant factor creating a status quo bias in

[3] Electricity, landline telecommunications, and home insurance.

switch decisions for certain groups, the information obstacle is less obvious here due to the transparent price structure. However, in an empirical study on the Swedish electricity retail market, Sturluson (2003) suggests that both switching costs and search costs are significant in determining consumer behavior with switch costs of major importance. An additional although different information perspective is that of how and to what degree households perceive the potential savings from switching, thus denoted as a "pull-effect" (that attract households toward a switch due to economic benefits) in our theoretical framework. In a study on the British electricity market, Flores and Waddams Price (2013) find that increased confidence in perceiving potential gains from switching increases search activity among those who already expect a gain from switching. This is in line with a study by Ek and Söderholm (2008) on the Swedish electricity retail market, which finds it more likely that households with a potential large economic benefit from switching will do so.

Studies that add social interconnection (defined as a "status-quo-effect" in the theoretical framework) as a rationale for consumer choice decisions have been widely recognized in fields ranging from economics (Bertrand et al., 2000) to the adoption of new technology by households (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2014). As an example, Bollinger and Gillingham (2012) demonstrate an effect from nearby adoptions of solar photovoltaic cells (PVs) on the general frequency of adoption of PVs in the surrounding community: consumers are more likely to adopt solar panels if neighbors install such panels. This is referred to as a neighbor-effect or peer-effect. In addition, social environmental concerns can influence individual environmental behavior (Park and Sohn, 2012). Thus, any environmental concerns can potentially induce a switch activated by a "pull-effect" towards a more environmental friendly alternative.

An additional "status-quo-effect" to rationalize resistance in households' switch decisions can be linked to specific market design issues. In this specific market, there are long traditions of vertical integration between local distribution companies and the incumbent electricity retailer, particularly with regard to the exclusive right held by the incumbent to issue a combined invoice[4] for the two services provided. Hope (2007) states that the challenges and potential distortive effects of vertical integration on competition were seen as an important issue in debates before and during the design and implementation of a market for electricity retailing. As a result of these considerations, a proposal to evaluate the single billing advantage held by the incumbent was put forward and considered by the Government in 2005. Later, a proposal to revise single billing took effect from the fall in 2016[5]. However, no previous attempt has been done to empirically evaluate the effect from single-billing on households' switch decisions.

All in all, the studies referred to above provide collectively strong support for there being a pervasive mixture of both economic and psychological influences in households' decision to switch

[4]A combined electricity bill consists of two parts: electricity costs and network tariffs.

[5]This study analyzes the period prior to 2016.

retailer. Of which the influences are triggered by both "pull"-effects, "push"-effects, and "status quo-effects".

## 3 Survey sample

This study uses a survey dataset collected for the Norwegian Water Resources and Energy Directorate (NVE) by IPSOS MMI between January 24 and February 11, 2013. The extensive survey was carried out by the authority in an attempt to gain new insight into households' adjustment, knowledge, and awareness related to their electricity consumption. We use the NVE dataset to analyze, distinguish and learn more about the determinants of importance in households' switch decisions. The sample of 1108 respondents was drawn from a pre-recruited Internet panel[6] of approximately 50 000 individuals representative of the population that has Internet access. These types of webpanels, where respondents voluntarily join, are defined as non-probability online panels, and are the most common form of webpanels (Callegaro et al., 2015). Such a non-probability panel comprises people with the necessary know-how and technological devices [7] enabling them to acquire knowledge of the various available contract prices. After 2013 one can assume that a larger proportion of households posses the same characteristics as do members of such a panel. Furthermore, Figure 2b shows that the average yearly switch rate has increased since 2013. This underpins the assumptions that ability to search for a competing retailer is getting more alike among all households compared to the panel from 2013.

Using an Internet panel for surveys has general advantages because of the cost effectiveness related to the opportunity to reach a large number of respondents; shorter turnaround time relative to traditional surveys; and an instant update of the database as respondents complete the survey, which allows for post fielding and instant access to results. However, there are disadvantages related to this approach that should not be underestimated. A study by Tsuboi et al. (2015) found that the estimated characteristics of commercial Internet panel surveys were quite different from national statistical data, indicating a problem of external validation of the results outside the population of the Internet panel. This methodological issue is highly relevant when interpreting results. It is especially important not to underestimate the potential bias that questions of a technical nature create, as the Internet sample has predefined knowledgde about the Internet. In other words, respondents are likely to have a bias toward technical skills compared to the population in general. In the questionnaire there are several questions related to households' skills in searching for information. Potential biases must therefore be considered when interpreting the results.

[6]The sample was stratified according to age, gender, and education, and selected at random from the pre-recruited Internet panel.

[7]This may be due to the bias toward higher income and higher educational level in the study sample. This will be discussed below

An additional source of concern is the potential bias from respondents engaging in reward programs. This can, according to Hays et al. (2015), undermine the data integrity. Respondents recruited via such reward programs can have a bias or a nonchalant attitude in the way they engage, evaluate and eventually answer questions in a survey. This calls for caution when generalizing results outside the survey population for the purpose of policy design recommendations.

Other than being a part of the Internet panel, essential criteria for respondents to participate in the study were responsibility for buying electricity to own household, lived in a house or an apartment, and were over the age of 20. Respondents were allocated so that approximately 60 percent lived in a house, while 25 percent lived in an apartment. The housing options *dorm* and *shared housing* were excluded due to the fact that one cannot say with certainty that respondents living here manage their own electricity contract. The housing type proportions are representative of the actual population.

Table 1 shows the socio-demographic profile of the sample. Compared to data from Statistics Norway (SSB), the sample is biased toward the more highly educated (65.4 percent in sample versus 35.6 percent in the wider population), and households with higher incomes[8]. Furthermore, the sample has a higher percentage of households with children; 41.4 percent compared to 27 percent in the actual population, registered in January 2016[9] Statistics-Norway (2016).

Figure 4 shows the age distribution of the sample. Compared to the actual population, the age groups 40-49 years and 20-29 years differ. That is, there is a bias towards respondents aged 40-49 years, with 19.6 percent in the actual population versus 32 percent in the sample. In contrast, the age group 20-29 years is underrepresented, with 17.8 percent in the total population versus 5.7 percent in the sample. The age bias in this group is likely due to numerous students and tenants in the 20-29 age group who are not responsible for buying their own electricity.

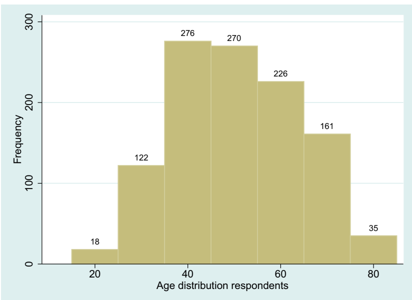



Figure 4: Sample age distribution

[8]Average income for actual population was according to SSB stable around 520' in 2013-2018

[9]It is not likely that this has changed significantly since 2013.

Table 1: Descriptive satistics of the survey sample in percentages

| Variable | Percent |
|---|---|
| Gender Content (men) | 50.5 |
| Married/cohabiting | 77.9 |
| Education (years) | |
| *High-school or less* | 32.0 |
| *University* | 65.4 |
| *Student* | 2.00 |
| *Undisclosed* | 2.6 |
| Household with children | 41.4 |
| Household annual income (1000 NOK) | |
| *100 or less* | 0.7 |
| *100 -199* | 1.5 |
| *200 - 299* | 3.1 |
| *300 - 399* | 8.0 |
| *400 - 499* | 11.0 |
| *500 - 599* | 10.7 |
| *600 - 799* | 18.5 |
| *800 - 999* | 21.2 |
| *1000 or more* | 18.1 |
| *Undisclosed* | 6.1 |
| *Not sure* | 1.2 |

An additional bias that needs careful handling is the likely existence of a potential self-selection bias: having Internet access implies that households have more sophisticated technical skills than the overall population. Although the self-selection bias in questions that cover technical skills is not considered to be of any major importance in the results, it nevertheless demands consideration when interpreting results.

# 4 The survey, responses and classification of statements

## 4.1 Survey design

The theoretical concepts in section 2 are recognized in the questionnaire and operationalized to measurable variables. This section presents the data, and classification of statements in line with the proposed theoretical framework outlined in Figure 1.

The survey was conducted in two steps. The first phase involved a pilot study with approximately 100 respondents, which was eventually included in the main sample of 1108. The survey was sent out to respondents by e-mail with the specifications and clarifications attached in a cover letter, and friendly reminders were later sent out to encourage respondents to complete the survey. The response rates from the pilot and main survey were respectively 24 percent and 23 percent. Six respondents started to answer but did not proceed through all questions, 235 respondents opened the survey but did not proceed. Due to a general decline in response rates to surveys in recent years, this is considered a normal response rate for such a comprehensive survey (Dillman et al., 2009).

The questionnaire consisted of two main parts. The first part covered background demographic information related to age, geographic affiliation and centrality of residence, income, education, marital status, number of children in the household, type of housing, and the total number of people in household. The main reason for obtaining such data is that the study hypothesized that this information could help to address the variation in decisions to switch electricity retailers. Part 1 of the questionnaire was followed by a screening question to remove respondents who were not responsible for buying electricity for their own household. Certain respondents may have had electricity included in their monthly condo fee, meaning that their electricity contracts were outside their control; for instance they may have been administered by their condo association. According to Statistics Norway (2013) 88 percent of households are responsible for their own electricity contract, 6 percent have electricity costs covered through some kind of condo fee and 6 percent specify other reasons for not buying their own electricity.

In the main part of the questionnaire, respondents were asked questions related to electricity habits and preferences in energy related issues, including environmental concerns related to energy use. Some questions were cut-off questions from others, and are therefore not included as variables in the econometric model. All questions had a closed form; they required respondents to select an answer from a set of choices (Krosnick and Presser, 2010). In certain questions respondents were asked to tick one alternative that was most in line with their opinion or understanding of the question. Statement questions related to knowledge and habits in energy-related questions were rated using a 6-point scale[10]. Following Krosnick and Presser (2010) this is common for this kind of survey. Only a few questions used a dichotomous or dichotomous scale *(Yes, No, Undecided)* .

In the questionnaire, respondents were asked about the status of their switch activity as follows; "Have you or anyone in your household ever switched electricity retailer since 1991"[11]. The question offers a trichotomous menu of alternatives: *yes, no, and not sure*, and shows that less than 60 percent had changed retailers while 5 percent reported that they were not sure. In this study this

[10]One point on the scale is "undcided"/"not sure".

[11]When competition was first introduced under the new Energy Act.

question was modified and conceptualized as a measurable dependent binary variable, *switch* taking the value 1 for switch and 0 otherwise. The few "do not know" answers were included as No-answers; i.e., the study considers not being aware as representing an unclear motivation to switch.

Due to non-systematic single-question non-response, plus an exclusion of respondents not part of the target population of the study i.e. not identifiable as responsible for choosing their electricity retailer, sample size $n$ varies across the items of the survey.

The next section summarizes the statements and response allocations of specific questions considered to have potential relevance in explaining households' motivations to switch electricity, of which some are discussed here.

## Responses

Immediately after opening up the end-user market to competition, a lively debate developed related to single-billing (see for example Hope (2007)). The criticism and concern was specifically aimed at former incumbents' roles as full-service providers of electricity and grid-services, and specifically at the "exclusive" right to issue a combined-invoice[12], hereafter termed single invoice.

Among the questions in the questionnaire, one enables measurement of the actual effect of a preference for a single invoice on switch decisions. The expectation was that there would be a higher frequency of switching among those reporting that they did not have a single invoice. However, as shown in Table 2 there is no perfect correlation between *single invoice* and *switch*. In addition, Table 2 shows that even households that have made a switch seem to favor an internal shift to an alternative contract offered by the incumbent retailer. Thus, these numbers adds to the suspicion put forward by Hope (2007), that the structural framework of this market represents a bias to the incumbent due to "exclusive rights" as full service providers.

A significant proportion of households reported that they had switched once or numerous times since 1991, and received a single invoice. In other words, the segment of the population receiving a single invoice was not truly bounded by a bias that prevented them from switching.

Table 3 shows the allocation of contract types in the sample[13] as obtained from questions in which respondents were asked if they were aware of what type of electricity contract they had. The answers are in line with the actual allocation in the population. That is, the majority had a spot price contract, a substantial portion had a variable price contract, and a small percentage held a fixed-price contract.

[12]Grid-service fee and electricity costs in one invoice.
[13]A detailed description of the different contract alternatives attached to help respondents distinguish contract types.

Table 2: Overview of Switching and receiving a combined invoice

| Switched retailer / Receive a combined invoice | No, household does not receive a combined invoice | Yes, household receives a combined invoice | Total |
|---|---|---|---|
| No, household has not switched retailer | 28 | 341 | 369 |
| Yes, household has switched retailer | 99 | 202 | 601 |
| Total | 427 | 543 | 970 |

n = 970

As expected, there was a higher percentage of switchers among households holding a spot price contract[14]. Furthermore, Table 3 shows that there were equal proportions of households that had switched and had not switched in the variable price contract segment. This is likely due to an internal transfer from a default contract to a market price plus contract.

Table 3: Switch allocation (percent) per contract type in sample

| Contract | Percent of Households | No Switch | Switch | Do not know |
|---|---|---|---|---|
| Spot price contract | 44.9 | 27.3 | 71.1 | 1.6 |
| Variable price contract | 25.1 | 48.5 | 48.5 | 3 |
| Fixed price contract | 6.4 | 52.9 | 41.4 | 5.7 |
| Other | 3.8 | 48.8 | 46.3 | 4.9 |
| Don't know | 19.9 | 32.3 | 50.7 | 17.0 |

n = 1093

In general, the responses reflected a good knowledge within the sample of how to acquire information and a good knowledge of how to switch. This implies that the available information at the official price comparison site and available information on how to switch were perceived by households. A little less than 53 percent of respondents who had not switched answered that they knew how to switch. This implies that there must be other reasons why this group did not switch. 11 percent answered that they did not know. The responses were more or less equally distributed related to knowledge on how to search for information on electricity prices. Only 20 percent of the non-switched households answered that they would have switched if it was easier. Therefore, there did not seem to be any information obstacles influencing non-switching behavior in this group, and more than 55 percent held the opportunity to receive a single bill as an important factor in their switch decision. It is interesting to note that 46 percent of this group preferred to buy electricity from a local retailer. In addition, loyalty is a potential factor affecting the propensity to switch. Less than 30 percent agreed (totally or partly) that households browse the Internet for

[14]Question is asked in relation to switch question

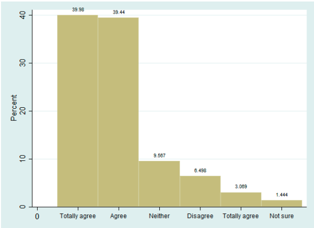
information on energy and energy-related products.

Measuring the degree of flexibility in electricity consumption show that nearly 45 percent have a positive attitude (totally or partly) agree to alter electricity consumption if it saves costs. Furthermore, less than 30 percent agree (totally or partly) that it is too much hassle related to energy saving. Only 12 percent (totally or partly) agree that there is little one can do to influence own electricity use. These answers give the impression that a majority of households knows measures to save energy, and in general are aware of own electricity use and how to influence it.

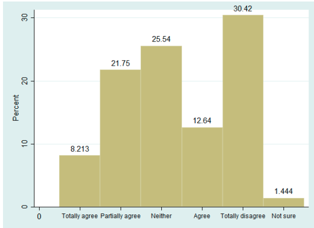
Furthermore, the respondents' statements show that more than 50 percent (totally or partly) agreed that electricity prices were too high. Less than 20 percent agreed (totally or partly) that electricity prices were fair. Furthermore, less than 15 percent were willing to pay more to avoid peak prices. This corresponds well to the numbers of households holding a preference for a fixed-price contract. However, comfort seemed to outweigh the importance of costs. Fifty percent of respondents agree (totally or partly) that comfort is more important than cost. This corresponds well with the product characteristics of electricity as a necessity good, and expectations that demand for such a good is more or less inelastic to changes in income. As shown in Figure 5a, an overwhelming majority were aware of costs. That means that households should be able to compare and evaluate potential savings from other contract offers, which could be an important factor in their switch decisions.

Environmental concerns seemed to be a stronger motivation to reduce consumption of electricity than reduced costs. Roughly 48 percent agreed (totally or partly) that reduced electricity use is worthwhile if it saves the environment, while 33 percent totally or partly agreed that it is worth changing consumption patterns to reduce electricity costs.

Figure 5b shows the allocation of responses related to feelings of loyalty towards the current retailer. Around 30 percent had loyalty feelings (totally or partly) toward their current retailer, while approximately 40 percent disagreed (partly or totally) that they felt loyalty. Furthermore, Figure 5b indicates segmentation into two groups, one being loyal and one group having no such feelings. This is in line with the findings of von der Fehr and Hansen (2010).




(a) I am aware of the size of my electricity costs




(b) Distribution: Loyalty towards current retailer

Figure 5: Statement responses

Statements related to the importance of peer effects show that 20 percent totally or partly agreed that they acquired information about energy-related products from discussion with family and friends. This relatively low degree of interaction in discussion casts doubt on peer effects as an important determinant in switch choice. The evolving literature on the importance of peer effects on consumer decisions to take action and indicates the importance of including this perspective in the study.

Table 4 provides descriptive statistics that show a high frequency of loyalty among non-switchers compared to switchers. This is in line with expectations that loyalty is an important factor in switch decisions. However, for the purpose of estimating switch behavior, the phrasing of the question makes it hard to distinguish loyalty to the current retailer from loyalty to the incumbent, meaning that the question cannot be operationalized as a variable to determine the effect of loyalty on switch behavior. Responses related to feelings of loyalty as a rationale for not switching were nevertheless high among non-switchers.

Table 4: Overview of Switch behavior and loyalty to supplier

| Household switched retailer/ Loyal towards current retailer | Agree | Undecided | Disagree | Total |
|---|---|---|---|---|
| No | 174 | 93 | 101 | 368 |
| Yes | 123 | 325 | 148 | 596 |
| Total | 418 | 249 | 297 | 964 |

n = 964

Table 5 lists the statements (categorized according to the theoretical framework outlined in Figure 3) in each category of the 6-point scale.

Table 5: Proportion of statements in each category of the 6-point scale

| Statement | Totally agree | Partially agree | Neither Neither | Partially disagree | Totally disagree | Not sure |
|---|---|---|---|---|---|---|
| **Information issues** | | | | | | |
| In my opinion the electricty bill provides a good overview of how costs are calculated | 27.6 | 39.0 | 16.9 | 8.00 | 2.8 | 5.7 |
| I trust information received from the energy sector | 13.3 | 36.9 | 30.1 | 11.5 | 5.5 | 2.7 |
| I know how much electricity and energy I use | 28.0 | 42.2 | 14.7 | 9.3 | 4.5 | 1.4 |
| I know how much my electricity costs are | 40.0 | 39.4 | 9.6 | 6.5 | 3.1 | 1.4 |
| I browse the Internet for information on energy and energy-related products | 8.9 | 18.7 | 29.3 | 19.4 | 21.1 | 2.5 |
| It is too much hassle to switch, related to energy saving | 6.3 | 20.3 | 31.1 | 24.8 | 14.4 | 3.2 |
| **Economic benefits** | | | | | | |
| Comfort is more important than to cost | 9.2 | 39.0 | 25.3 | 20.0 | 5.3 | 0.8 |
| I am willing to accept an average higher price in order to avoid peak prices | 1.8 | 11.6 | 32.5 | 25.1 | 24.0 | 5.1 |
| I am willing to alter electricity use if it reduces my electricity costs | 12.9 | 31.2 | 23.4 | 17.5 | 12.0 | 3.0 |
| I am familiar with simple measures to reduce electricity consumption | 27.6 | 47.7 | 15.7 | 6.0 | 1.6 | 1.4 |
| In my opinion the electricity bill prices in general are too high | 29.2 | 25.1 | 23.6 | 14.4 | 5.3 | 2.4 |
| I cannot influence how much electricity I use | 1.5 | 10.1 | 18.3 | 33.8 | 35.0 | 1.2 |
| **Peer effects** | | | | | | |
| I get information about energy-related products from discussion with family and friends | 3.2 | 16.1 | 26.7 | 22.7 | 29.0 | 2.4 |
| **Environmental concerns** | | | | | | |
| I am willing to reduce electricity consumption if it saves the environment | 12.27 | 36.2 | 26.9 | 14.3 | 8.9 | 1.4 |
| I am willing to change electricity use during the day if it saves the environment | 8.5 | 25.4 | 27.6 | 20.4 | 15.1 | 3.1 |
| **Loyalty** | | | | | | |
| I feel loyalty towards my current retailer | 8.2 | 21.8 | 25.5 | 12.6 | 30.4 | 1.4 |

## 5 Switch response model

Based on the above discussion, this study adopts the following categories of factors that is considered as to influence households' choice to switch as can be specified in Function 1:

$$P(switch) = f\,(\textit{market structure, information issues, economic benefits, peer effects, environment, loyalty}) \quad (1)$$

Where $P(switch)$ expresses the consumer's propensity to switch (which is a measure of choice) interpreted as an index determined by a function $f$ affected by the factors discussed in section 2. The relationship defined in Function 1 is the starting point for structuring statements and eventually including variables in the econometric model to determine factors that influence households' switch decisions in line with the theoretical framework. The dichotomous variable *switch decision* is the dependent variable.

The study adopted a probit model for binary responses to explain the effects of the independent variables on the probability of the average respondent to switch. The model characteristics are such that the standard normal cumulative distribution function (cdf) is strictly between zero and one for all parameters (Wooldridge, 2016). This yields the model:

$$switch_i = \beta_0 + X_i\beta + \epsilon_i \quad (2)$$

where switch is a binary variable equal to one if household $i$ has switched, and $x_i$ is a vector of explanatory variables from the survey . $\epsilon_i$ is an error term.

The model structure and interpretation is as follows: The dependent variable (or switch indicator) is equal to 1 if a household performs a switch and 0 otherwise. The probit estimation reports coefficients as probabilities, while average marginal effects[15] are included to evaluate the magnitude of estimated coefficient value of the probability to switch. The partial derivatives are interpreted as the change in the probability of switching as a specific variable increases by one unit. Furthermore, the signs of the coefficients report the direction of the probability of switching; i.e., a coefficient with a negative sign has a negative effect on switch probability and vice versa for a positive sign. In the case of dummy variables, probabilities are calculated based on a discrete change in the dummy from 0 to 1. Corresponding average marginal effects are interpreted as the change in the probability of switching as the dummy changes from 0 to 1.

The model was determined by a backwards reduction approach[16].Table 6 displays the estimation results, coefficients and marginal effects derived from the final model estimation that includes the

[15]From averaging the individual partial effects across the sample.

[16]See for example Osborne (2000) for a more in-depth description of various approaches for entering variables into a multiple regression model, hereunder the backwards reduction approach. A general-to-specific (GETS) algorithm ap-

following variables: $County$ is a dummy variable which takes a value of 1 if respondent lives in a rural area, such as the countryside or sparsely populated community, and 0 otherwise. *Children* denotes the number of children in the household, *Single-invoice* is a dummy variable taking a value of 1 if household receives one combined invoice, and 0 otherwise, *Single-invoice* stemming from a dichotomous question in the questionnaire. *Internet for information* represents how prone respondents are to search for information on electricity-related issues online. Internet for information is a variable derived from the statements under category "Information issues". The variable was modified and conceptualized from a 6-point scale variable to a measurable variable having two categories; disagree and agree. Hence, we estimate the model:

$$\begin{aligned} switch_i = \beta_0 + \beta_1 county + \beta_2 children + \beta_3 singleinvoice + \\ \beta_4 internet - agree + \beta_5 internet - disagree + \epsilon_i \end{aligned} \tag{3}$$

The results from this cross-sectional study gives a snapshot of households propensity to switch electricity retailer based on this specific dataset, and the regression results specifies to what extent the independent variables in the model affect the propensity to switch.

From the theoretical framework outlined in Figure 1 and further elaborated throughout the paper, the analysis argue that a decision to switch from a current service provider is driven by "push"-effects, "status-quo"-effects, and "pull"-effects. Although (1) shows that the probability to switch is a function of six factors, the model with the best fit does not include all six types of variables. Hence, the chosen method does not capture all six factors from the current dataset.

The detailed estimation results are shown in Table 6. Results show that respondents who received a single invoice were less likely to switch. This noticeable result adds to the suspicion that the privileges held by former vertically integrated companies seem to have been disruptive to securing full mobility of consumers, in line with the concerns raised by Hope (2007) relating to the initial design of this market. Evaluated from the perspective of the theoretical framework in Figure 3, the single billing-effect is a status quo bias stemming from a market design issue. In addition, it relates to the psychological rationale caused by the status quo bias and loyalty to the incumbent, as discussed by Klemperer (1987), and the notion that consumers favor the incumbent firm.

proach following the logic in Hendry and Krolzig (2004); Campos et al. (2005) suggests the same overall model specification. Another way to validate the model would be to test it against another dataset using an identical questionnaire. However, this is outside the scope of this study.

Table 6: Determinants of the propensity to switch electricity retailer

| Variables | Coef. | Std.err. | p | Marginal effects | Std.err. | p |
|---|---|---|---|---|---|---|
| Constant | 1.486 | 0.146 | 0.000 | | | |
| County=1 if rural | -0.027 | 0.009 | 0.005 | -0.007 | 0.002 | 0.004 |
| Single invoice | -1.785 | 0.121 | 0.000 | -0.465 | 0.016 | 0.000 |
| Children in household | 0.132 | 0.051 | 0.009 | | | |
| Internet for information | | | | | | |
| Agree | 0.340 | 0.133 | 0.010 | 0.089 | 0.035 | 0.010 |
| Disagree | 0.090 | 0.122 | 0.460 | 0.024 | 0.032 | 0.460 |
| N | 811 | | | | | |
| AIC | 763.09 | | | | | |
| BIC | 791.28 | | | | | |
| LnL | 327.79 | | | | | |
| Prediction (percent)) | 77.31 | | | | | |

Furthermore, it is interesting to note that respondents who agreed that they searched for energy- and electricity-related products were more prone to switch suppliers. These results demonstrate that more search activity among "searching" households increase how prone they are to switch. This finding is in line with those of Ek and Söderholm (2008), who reported that households with high search costs and difficulties in perceiving potential gains from switching were less likely to switch. On the contrary, insignificant result for households' not searching for information on propensity to switch may imply an inherent resistance to switch from factors related to "status quo"-effects not stemming from information obstacles.

The results show that the number of children in a household increased the likelihood of switching electricity suppliers. This finding can be related to economic benefits as a "pull"-factor to induce a switch from the current situation. Clearly, a larger household has higher electricity expenses, and the benefits from switching are larger.

The central versus rural geographic affiliation diversified was significant. The results suggested that on average a respondent in a rural area is less likely to switch. Although the differentiation of this variable was not sufficiently sophisticated to differentiate between specific geographic areas, the results indicate that households in rural areas are more bound by their current situation. This may be due to stronger local traditions and feelings of loyalty towards the local power company. This finding is in line with the findings of Defeuilley (2009) and the hypothesis that sticky consumers remain loyal.

Throughout all the model specifications, peer effects and social interconnection did not appear to be significant in affecting switching decisions. Neither did any of the environmentally motivated statements. The lack of significant determinants motivated by environmental concerns can potentially be related to the widespread recognition of electricity as an environmentally friendly source of energy in Norway. Almost 100 percent of electricity generation in Norway stems from hydro power or other renewable energy sources, which make Norway stand out across electricity retail markets.

## 6 Conclusion and policy implications

Using data obtained from an Internet panel survey collected by NVE in 2013, this study analyzed determinants for households' decisions to switch electricity retailers. The analysis starts off with a theoretical framework that embraces "pull"-effects, "push"-effects, and "status-quo"-effects to analyzing households' switch decision.

The study adds new insights about consumer behavior in one of the first electricity retail markets by hypothesizing that the propensity to switch is influenced by both economic- and psychological factors. The study rejects the null hypothesis that neither economic nor psychological influences alone affect the propensity to switch.

From a market structure perspective, the primary results suggest that allowing certain retailers, mainly former vertical integrated retailers, to hold certain inherited privileges has been disruptive to securing an efficient market and kept a substantial amount of households in their current situation. Although this inefficiency issue has been an object of discussion among policy makers, no study so far has empirically explored the effect of single invoicing on households' activity in the market place. Our results suggest that single invoicing has been disruptive in securing a competitive market, emphasizing the crucial importance of equal conditions for incumbents and entrants in the market so that the premises for an efficient market outcome are in place.

Furthermore, results show that households in rural areas seem to be less prone to switch than households located in urban areas. This adds weight to the suspicion that regional differences seem to be a driver behind consumer choice in this market in line with the findings in Mulder and Willems (2019) on the Dutch retail market. In addition, results indicate that search activity for energy-related issues seem to influence the propensity to switch for the average household. This finding demonstrates that although information is available through on-line price listings, there is a considerable potential to increase switch activity by encouraging increased search activity.

Thus, findings highlights the importance of looking beyond and bringing in the complexity in households' switch decision as to correct for and gather new and more refined insights into potential sources of reluctance to switch so that these can be targeted with the most effective policy measures to facilitate an efficient expansion of the electricity retail market in the long run.

In addition, the study sheds light on an important methodological issue related to potential selection bias in Internet panel surveys and the use of such surveys for policy design purposes[17]. Thus, it is likely that the effect of increased search activity on the probability of switching is even stronger outside the sample population due to the selection bias in the Internet panel survey. Furthermore, it is likely that questions of a technical nature will have a bias due to the sample population having a higher technical competence than the population in general. It is important to be aware of the selection bias in Internet panel surveys and the numerous sources of bias related to such panels stemming from careless responses, and rapid answers, in addition to the technical knowledge bias.

That said, questions of a non-technical nature and general demographic factors are likely to be representative of the population in general, and thus are important in demonstrating the factors determining for households' decisions to switch electricity retailers in one of the first electricity markets to undergo liberalization. The information gained is thus of relevance for other countries still in the process of electricity market liberalization.

## Acknowledgments

Valuable help and comments from Elise Øby, Bjørnar Karlsen Kivedal, Kristine Grimsrud, Kyrre Rickertsen, Olvar Bergland and Judy McDonald are gratefully acknowledged. Any remaining errors, however, reside solely with the author.

[17]NVE's report does not discuss and take into consideration the external validation of the Internet survey responses

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# Paper III

# Electricity Retailing and Price Dispersion

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August 30, 2021

**Abstract**

This paper identifies price development in electricity contracts evaluated from the theoretical expectation that prices for homogeneous goods converge according to the "law of one price" such that there is no price dispersion. Results indicate a substantial degree of price dispersion and that prices fail to converge. By estimation of the long-run relations and their dynamics, the study identifies that dispersion in specific electricity products seem to be strengthened as more firms enter the market, while increased consumer switching has the opposite effect. Thus, findings provide evidence of market imperfection in the electricity retail market and the possible sources behind it. The study builds on well-established theoretical models to rationalize price dispersion in homogeneous product markets and adopts a novel empirical approach through a vector error correction model (VECM).

**Keywords:** Electricity retail market, price dispersion, Norway
**Submitted to:** Energy Economics (resubmit)

## 1 Introduction

Informal observations of prices in the end user market for electricity show that prices differ across seemingly similar contracts. Thus, causal observation contradicts simple textbook models of competitive markets for homogeneous goods and the idea that an efficient market outcome will obey the “law of one price”. On the contrary, as shown in a vast and growing literature in industrial organization, and as demonstrated in an early study by Varian (1980), “the law of one price” is no law at all. That is, price differences in homogeneous product markets are not necessarily a sign of inefficient markets.

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This study explores price development in an end-user market for electricity and unravels whether prices converge according to the law of one price as dispersion in prices gets smaller over time. Price dispersion, as defined in economics, refers to variation in prices, within a short time interval, across retailers offering identical products. Dispersion in prices is thus expressed as the distance between the highest and lowest prices in the sample at a given time. In traditional commodity markets such price differences are typically attributed to costly information gathering among consumers or differences in the service provided by retailers offering the product.

Three crucial elements distinguish the Norwegian electricity market from traditional commodity markets: i) electricity may be viewed as a homogeneous good providing uniform quality regardless of production source and because of severe limitations to product differentiation; ii) prices are available for comparison following an official on-line price overview since 1998; and iii) any fees associated with switching retailer and contract were eliminated some 20 years ago. Thus, there are no specific regulations in this market and retailing takes place according to the general Consumer Purchases Act.

Bye and Hope (2005) provide an excellent overview of the background to the deregulation of the electricity sector in Norway. In addition, numerous studies have analyzed more general outcomes from opening up to competition in the electricity retail market, where studies including those of Bye (2003); Bye et al. (2003); Johnsen (2003); Amundsen et al. (2006); von der Fehr and Hansen (2010); von der Fehr (2013) of significance. These studies add important information regarding efficiency outcomes from introducing competition in the end-user market for electricity. However, while these studies provide an excellent evaluation of the overall performance of the sector, there has been no previous attempt to empirically estimate the dynamics proposed by theoretical models that rationalize dispersion in electricity prices in this market.

The motivation for this study was that despite a long period since the introduction of crucial measures to secure transparency and costless switching, informal observations showed that price dispersion remains substantial in electricity prices. Price differences seem to prevail and may even have increased over time. This failure to converge implies that dispersion in prices continues to persist because of underlying factors, hitherto not identified for this market, which prevented the expected decrease of price dispersion over time.

Starting with the characteristics of electricity that conform the Marshallian notion of a homogeneous good Marshall (1922), and market characteristics already defined, this study aims to answer the following research questions:

1. Do electricity retail prices in this market converge according to the law of one price?
2. Are there any significant effects of adjustments in switch numbers/volume, electricity market price, and number of firms offering electricity contracts on price dispersion?

This paper explores the above questions from the perspective of a well-established clearinghouse model that matches the institutional characteristics of this market. The model adopted subsumes the theoretical models in the field, and specifically hinges on the model by Rosenthal (1980). The paper analyzes the hypothesis that price dispersion stems from differences in consumers' exogenous preferences, where one fraction of the consumers buy at the lowest listed price, while each retailer also has a loyal segment of consumers, labeled loyals, who are unaffected by price, market price development, and the number of firms offering the specific contract under study.

The rest of the paper is organized as follows. Section 2 presents previous studies. Section 3 background information and important market characteristics. Section 4 presents the data. Section 5 presents descriptive statistics followed by a presentation of the theoretical framework rationalizing price dispersion in section 6 and the empirical approach in section 7. Section 8 presents findings, and finally section 9 summarizes key findings and provides concluding remarks.

## 2 Previous studies

The question of price dispersion in deregulated electricity retail markets has been studied to some extent in other markets. However, less has been done to explore if prices converge over time.

Simshauser and Whish-Wilson (2017) analyze electricity prices in two Australian states and find that the deregulated state displays high price dispersion and marginal offers at break-even prices. Electricity prices are found to be less dispersed in the semi-regulated state where a price-cap exist, although the overall pricing is less efficient here. The study reveals that there is a misallocation of vulnerable consumers to high-cost contracts in the deregulated market, despite that the efficient pricing criteria of the marginal unit priced at marginal cost are met.

Nelson et al. (2018) extends the analysis by Simshauser and Whish-Wilson (2017) by considering electricity consumption to be heterogeneous. The study concludes that the heterogeneous nature of electricity consumption is a source of price dispersion, of which is strengthened as new products and services are introduced giving retailers an opportunity to price differentiate.

Gugler et al. (2018) study the German electricity retail market and price dispersion from the perspective of asymmetric interaction between the incumbent and the entrants, consumers' willingness to search for and switch to an alternative service provider, and the price discrimination strategy of the incumbent. The study finds that search intensity among consumers is a significant source of price discrimination. Hence, incumbent tariffs are higher in areas where consumers search more and vice versa in areas with less intense consumer search activity.

Mulder and Willems (2019) provide an in-depth analysis of the evolution of the Dutch electricity retail market for household consumers from 2004-2014. The study emphasizes that price differences between retailers remain whilst a large fraction of consumers do not take active part in the market.

In contrast to the existing literature, this paper takes the approach to explore price development over time and to identify what variables that drive dispersion in the long run. The paper provides new empirical insights into price development in the different contract segments from the view of an experienced deregulated electricity sector by addressing price dispersion from a twofold approach. First, the study analyzes how price dispersion has developed from a descriptive approach in line with Baye et al. (2004) and their study on price dispersion from an Internet comparison site. This approach unravels whether price dispersion is a disequilibrium that is corrected over time as consumers adopt, adjust, and learn[1]. In the second approach, the paper introduces a theoretical model first outlined by Rosenthal (1980) to rationalize price dispersion when price information is readily available for comparison at zero search costs. Third, the dynamics outlined in the theoretical model are structured in a vector autoregressive (VAR) model as to obtain any long-run dynamics affecting dispersion in prices.

The analysis assembles a rich and novel data set of weekly electricity contract prices obtained from the Norwegian Competition Authority (NCA), quarterly data on the number of switches of retailer from the Norwegian Water Resources and Energy Directorate (NVE), and weekly spot prices and monthly forward prices from NordPool.

## 3 Market characteristics

To set the stage for the study, this chapter provides essential background and market characteristics related to policy measures, contract types, and consumer preferences.

From a market design perspective the Norwegian electricity market follows the wholesale and retail markets model (Cretì and Fontini, 2019). Congestion in the national transmission grid is handled with a combination of dynamic price areas and counter-trade within price areas. In the restructuring process the vertically integrated utilities were split into generation, distribution and retailing with their existing customers assigned to the newly formed retailer.[2] End users are free to retain the incumbent supplier or sign a new contract with any other supplier offering a contract in a given municipality. Several retailers continue to serve only their “original” market while other retailers are offering contracts nationwide or to a limited geographical area within a price zone. This study includes only nationwide contracts.

Contractural terms such as entry into and termination of the contract, metering, pricing and ex-

[1] As sources of inertia become more moderate/less intervening over time.

[2] The degree of separation of the retailing business from the other activities is a contentious issue. Utilites with more than 100 000 customers in their grid are required to organize their activities in separate legal firms.

change of information for so-called standard contracts which comprise the following; a variable price product, for which the price is made up of a price per kWh set by retailers in addition to any fixed fees, a spot price product for which price components are the market price defined at Nord-Pool (thus the price fluctuates and directly reflects the spot price denoted the "system price") plus any mark-up and fixed fee set by retailers, and a fixed-price product for which price is set by the retailer for a fixed period of time and any risk evaluation regarding price is solely by the retailer. Such contracts are typically of 1 or 3 years duration. According to Olsen et al. (2006), the main difference between contracts is how prices are defined and expectations regarding fluctuations in prices, thus the risk profile. Whereas consumer preferences differ.

Following the Norwegian electricity market reform in 1991, households were assigned a variable price contract (the so-called default contract). If a household holds a different contract than the default, an active choice to switch has been made at a certain time throughout the period since opening up the market. Figure 1 provides a clear picture of the allocation of the standard contracts throughout the period, and shows that the major trend has been to switch away from the default contract to a market price contract. Whilst the number holding any of the fixed price contract was low and further decreased under the period.

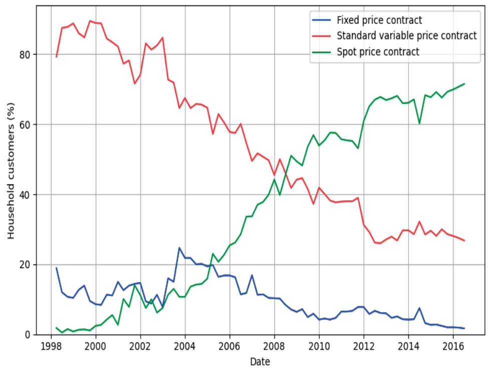


Figure 1: Allocation of standardized contracts. Source NVE.

In attempt to encourage switching, two measures were introduced early on; elimination of any fees associated with switching retailers in 1997 and mandatory reporting of standard electricity contract prices in 1998. As illustrated in Figure 2 elimination of any switch fees had an immediate effect on consumer switch activity as the number of switches increased noticeably after the introduction of these measures in 1997/1998. In 2000, around 50,000 households switched retailer in a quarter, representing roughly 8 percent of all households in Norway. Throughout the period 2000 to 2010 the switch volume stabilized at around 10 percent of all households; i.e. little less than 60 000 switches per quarter. Furthermore, there was an increasing trend after 2010; the switch volume reached 14 percent in 2015. These numbers indicate that a substantial proportion of households take an active part in the marketplace. However, the majority still do not search for an alternative electricity deal.

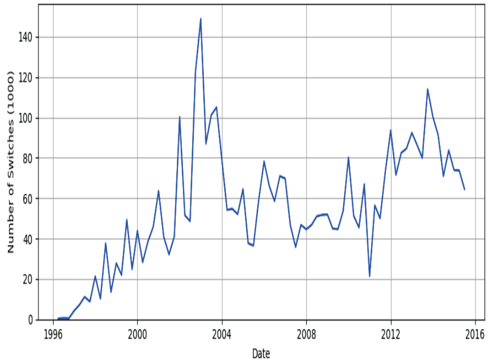


Figure 2: Number of households switching retailer in a quarter. Source NVE.

To show the dynamics relating to search activity on the price site, Figure 3 plots the number of search sessions on the price overview site and the system price as to illustrate the correspondence between prices and searching. It is likely that as consumers are informed of peaking electricity prices (especially in the winter when electricity expenses for heating purposes are major) for instance via media coverage, they are more likely to check the price overview. One such event happened in 2010 when electricity prices peaked during cold and dry winter months. Furthermore, Figure 3 shows that number of sessions drop toward the final years. A possible explanation may be that once households have made a switch, they stop watching prices for a while.

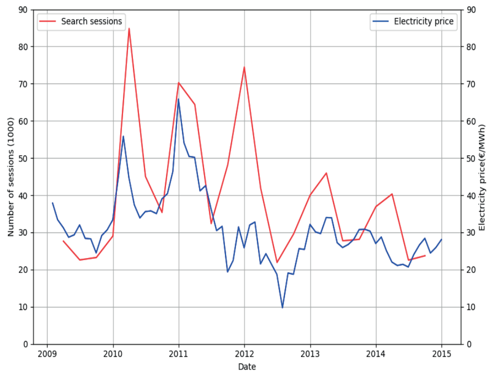


Figure 3: Number of search sessions and "system price" for electricity. Source NVE.

The correspondence between households browsing the price comparison site and fluctuations in the underlying wholesale price, indicates how sensitive consumers are to price changes before they start actively searching for better deals. Some consumers are more risk averse than others and accept a larger degree of price volatility. The most risk averse, on the other hand, are less willing to accept price fluctuations and have a preference for contracts with less volatile price adjustments. If one argues that there is - "packaging" of electricity into different contracts due to risk preference as described here, one can perhaps argue that electricity contracts can be considered as slightly heterogeneous products, distinguished by consumers' risk preference. However, from the research perspectives considered here, electricity is a homogeneous commodity within the different standardized contract segments, as the opportunity to differentiate the products was severely limited in the time frame of the study. This implies that, from a theoretical perspective, prices should not vary much within similar contract segments. However, although prices are readily available for comparison and there are no switching fees related to changing contracts or retailers, price dispersion in electricity contracts is pervasive and significant.

Although the increased migration to spot-based contracts imply that consumers take an active choice and participate in the market, Bye and Hope, (2005) argue "the absolute number of switching is not necessarily an appropriate indicator of increased competition. What matters is whether the number is sufficiently large to cause suppliers to set prices competitively." Migration to spot-based contracts in itself does not mean that dispersion in prices is reduced (or increased). Thus, the migration does reflect a maturing of the retail market that must be considered as essential background information to implement and understand findings in this study.

### Number of retailers and contracts

Figure 4 (A) plots the total number of retailers offering any type of standard retail contracts for electricity at the NCA price overview [3]. According to von der Fehr and Hansen (2010) the downward trend up until 2008 is mainly explained by mergers where large businesses take over smaller neighbors (often vertically integrated incumbents). The structural break in 2010 which allowed one retailer to have more than one of each contract type at the price overview, resulted in another downward trend in the number of retailers. It is likely that some of the changes can be explained by more mergers and some retailers leaving the business for other reasons. Figure 4 (B) shows the number of different firms offering a specific type of standard retail contract. As is clear from this figure there was a marked drop in all types of standardized contracts following 2010. Whereas the number of 3-year fixed experienced substantial reduction down to a little more than 20 contracts in total.

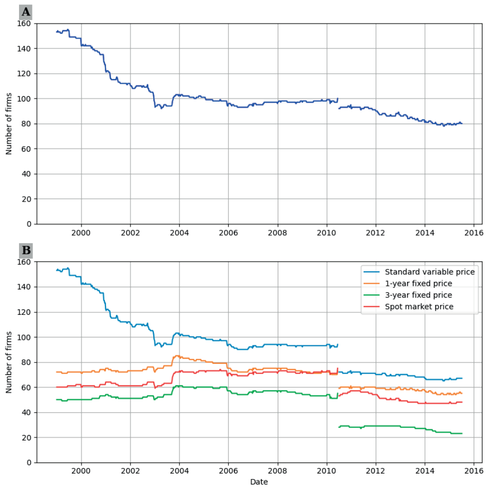


Figure 4: (A): Total number of different firms offering any type of standard retail contracts for electricity. (B): Number of different firms offering a specific type of standard retail contracts for electricity. Source: NCA.

With these market characteristics in place, the next section presents the data and the subsequent section, which represent the first approach to exploring price development in this market.

[3]The total number comprise firms offering nationwide as well as regional/local contracts.

## 4 Data

This study employs weekly time series data on electricity prices specified by contract (variable price, market price, and fixed price (1 and 3 years duration)) from week 1 in 2004 to week 28 in 2015 obtained from NCA. The sample comprises standard electricity contract actually traded in a specific week and valid in all price zones. Thus, per definition nationwide. Any special price contracts, prepaid contracts, and local/regional contracts are excluded from the sample.

The sample of firms offering standardized contracts included in this study are shown in panel (A) in Figures 5, 6, 7, and 8. Any fixed payments are handled such that a yearly average consumption of 20 000 kWh is distributed across contract prices. The mean price of the standardized contract prices is calculated as the average price in the sample. Spread is the difference between max and min price. Whilst dispersion is the standard deviation. All contract prices are unweighted.

There is a structural break in the data series for electricity prices in week 25, 2010 due to the introduction of product IDs, which allowed a retailer to have more than one of each contract type listed at the site. Prior to week 25 in 2010, retailers could only have one contract of each type registered under the same retailer ID so as to differentiate contracts to different consumer segments. Here the datasets are combined prior to and after the break to cover the whole period by aligning contracts according to the retailers unique organization number.

The electricity market price[4] and forward prices (1 and 3 months) were obtained from NordPool. Summary statistics of the data and corresponding measurement units are included in Appendix A.

The quarterly data on switch activity are from NVE and include the number of switches of service provider in a given quarter. Figure 2 plots the switch data.

Given the quarterly nature of the switch data, price data for the standardized contracts and weekly system price are made quarterly for inclusion in the econometric model.

## 5 First approach: Descriptive statistics

As outlined in the introduction, this paper investigates price dispersion in standardized contracts by using a twofold approach. In this section the descriptive statistics are presented to show price development in the specific sample of standardized contracts under the period of study. Thus, to explore the development in price dispersion over time.

[4]The "system price" from Nord Pool is used as the reference market price.

## Price development in standardized electricity contracts

Figures 5, 6, 7, and 8 present the plots of the sample of firms offering the specific standardized contracts and their price development between January 2004 and July 2015. All panels contain 4 figures, where (A) shows the number of firms offering this type of standardized contract; (B) plots the spread (maximum- minimum); (C) shows the mean, maximum and minimum price; and (D) shows the standard deviation for registered prices, also denoted as the price dispersion in the sample of this specific contract segment.

The sample plot in Figure 5 shows that as more firms offered a one-year fixed contract after 2010, there was a simultaneous increase in spread and price dispersion.

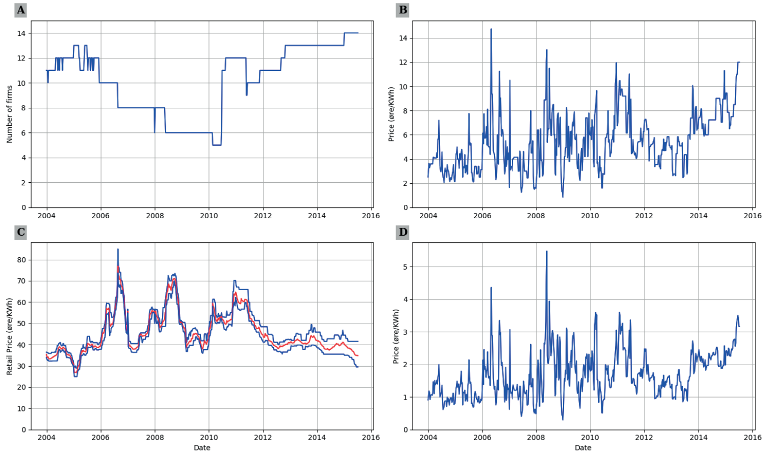


Figure 5: Registered prices for a one-year fixed price contract. (A): Number of firms. (B): Price spread. (C): Minimum, maximum and mean price. (D): Standard deviation. Source: NCA.

Figure 6 plotting registered prices for the three-year fixed price contract features more or less the same pattern as the one-year fixed price contract. However, the number of firms offering this contract is severely limited. Thus, the three-year fixed price contract segment will not be included in the econometric estimation of long-run relations.

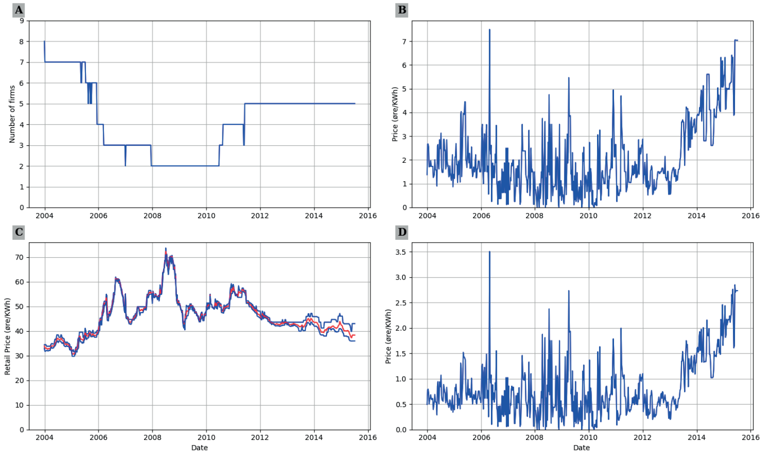


Figure 6: Registered prices for a three-year fixed price contract. (A): Number of firms. (B): Price spread. (C): Minimum, maximum and mean price. (D): Standard deviation. Source: NCA.

Plots of the market price contracts in Figure 7 indicate true dispersion in contract prices over the period under study, with an increasing trend over the last years. This coincides with an increasing trend in the number of firms offering this type of contract.

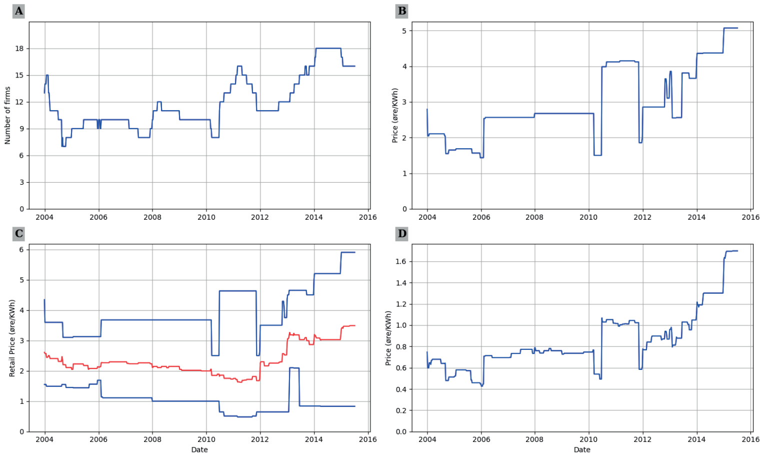


Figure 7: Registered prices for a spot price contract. (A): Number of firms. (B): Price spread. (C): Minimum, maximum and mean price. (D): Standard deviation. Source: NCA.

It is evident from Figure 8 that the sample of nationwide firms offering a variable price contract had a decreasing trend up until 2013, whereas the number of firms offering this contract type slightly increased. The general trend seen in Figure 8 (D) is that the dispersion has been occasionally noticeable high during specific weeks (typically related to high price periods in 2003/2004 and 2010). Featuring a less volatile pattern after 2010.

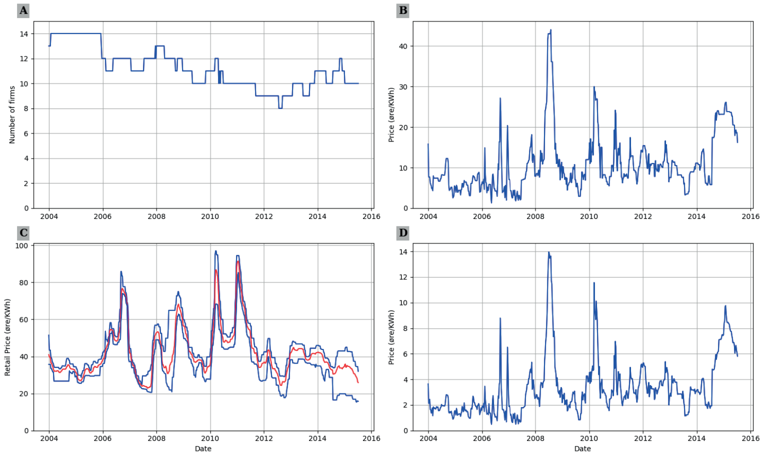


Figure 8: Registered prices for a standard variable price contract. (A): Number of firms. (B): Price spread. (C): Minimum, maximum and mean price. (D): Standard deviation. Source: NCA.

### Features from the descriptive statistics

There are especially three features that particularly stand out from Figures 5, 6, 7, and 8:

1. It is evident that the price dispersion for the different contract segments is not zero and has not declined. Thus the hypothesis that prices are converging can be rejected.
2. The plots of the market price contract indicate true dispersion. While the fixed price contracts of 1 and 3 years duration and the variable price contract do not fall under this strict definition of true price dispersion.
3. All series are trending. Thus they are potential I(1) processes and must be handled with care. Following Granger and Swanson (1997), a data series that appears to be non-stationary should be assumed to be non-stationary if there is no clear evidence for rejection of the assumed hypothesis that it is non-stationary.

Whereas plots of the data indicate a failure to converge according to the law of one price, this study seeks to disentangle these observations and determine whether switching, the underlying market price, and the number of firms offering a specific contract in a specific week are reflected in dispersion in prices. Which is exactly what the theoretical framework on clearinghouse models do. In addition, the analysis reveal whether there are any findings that indicate other potential factors -outside of the model framework that are potential sources of sustained dispersion in prices.

## 6 Theoretical framework

Clearinghouse models as a rationale for price dispersion were first introduced more than four decades ago by Salop and Stiglitz (1977). A growing literature, including studies by Rosenthal (1980), Varian (1980), Baye and Morgan (2002), and Baye et al. (2006), treats price dispersion in clearinghouse environments by using slightly different approaches. However, a common factor in all models are a rationalization of price dispersion by exogenous differences in consumer preferences.

There are a few key market characteristics that set the stage for choice of the theoretical model to define variables to include in the econometric model. Electricity prices are readily available at an official price comparison site, implying no search costs[5]. The comparison site is an intermediary between retailers and consumers, functioning as a clearinghouse. In addition, there are no fees associated with switching contract or retailer in this market.

Based on empirical data and a previous study by von der Fehr and Hansen (2010), it is evident that this market is nuanced, with one consumer segment that seeks the best deal, and another segment of passive consumers that typically stick to their incumbent retailer and contract.

The homogeneous product characteristics of electricity, combined with no switch fees and transparency in electricity prices, underpin the view that disequilibrium in prices are corrected over time. The model presented by Rosenthal (1980) gives a theoretical justification for persistent price dispersion in markets with an information clearinghouse; that is, markets where a third party provides consumers with a list of prices.

Finally, consumers are divided into two categories according to their exogenous differences in preferences; shoppers (actively seek the lowest listed price) or loyals (buy at a higher price for different reasons[6]).

[5]This context removes any theoretical search models as rationales to explain dispersion in prices for electricity.

[6]This includes difficulties in accessing the clearinghouse, psychological factors keeping them at the status quo, or difficulties in perceiving potential costs and benefits from switching retailers.

The Rosenthal model is applicable to the Norwegian electricity market for two main reasons: (1) it assumes a mandatory [7] and costless posting of electricity contract prices at the price comparison site; and (2) it assumes a diversified segment of consumers, already introduced as shoppers and loyals. This means that each firm has a mass L of "loyal" consumers. Below a modified version of the Rosenthal model, which was first presented by Baye et al. (2006), as to underpin the choice of variables to include in the econometric model.

### The clearinghouse model

Due to regulations that define a mandatory and costless reporting of prices to the official price comparison site hosted by NCA, the first assumptions in the general clearinghouse model presented by Baye et al. (2006) is fulfilled; it is costless to list prices, thus retailers will list prices with probability equal to 1.

The following equation describes the distribution of average prices $F(p)$ for a specific standardized contract under the period of study, under the assumption that the number of retailers vary.

$$F(p) = 1 - (\frac{(v-p)}{(p-m)}\frac{L}{S})^{\frac{1}{n-1}} \quad p \in [p_0, v] \tag{1}$$

$$p_0 = m + (v-m)\frac{L}{L+S} \tag{2}$$

where $m$ is the marginal cost for retailers, $v$ denotes willingness to pay, $p$ is the average price, $L$ is the number of loyal consumers such that $\frac{L}{L+S}$ is the share, $S$ is consumers seeking a competitive price, $n$ denotes the number of firms and $p_0$ is the average price defined by a given share $L$. Equations 1 and 2 show how the relationship between $L$ and $S$, create dispersion in prices stemming from differences in consumer type.

The willingness to pay differs between loyals and shoppers. Thus, loyal consumers expect to pay the average price charged by the sample of firms, whereas shoppers expect to pay the lowest price among available prices. This, in addition to adjustments in market price and number of firms entering the market, will potentially affect the magnitude of price distribution.

The hypothesis derived from Rosenthal's model, is that as the share of shoppers increases, the spread in prices will decrease and eventually converge. In addition, an increase in the number of firms $n$ will affect the distribution of expected prices paid by all consumers such that an increase in the number of firms will increase the expected transaction prices by all consumers hinging on Rosenthal's assumption that entry brings more loyals into the market and shopper accounts for an increasingly small account of total consumers.

[7] Retailers will post prices with a probability equal to 1.

The share of shoppers and the magnitude of switch activity in a market for a given period cannot be assumed to have a 1 to 1 correspondence. One shopper may switch more than once, implying a larger magnitude of switch activity than the share of shoppers. However, an additional switch performed by a particular shopper will not result in the shopper being worse off. The data on switch activity as adopted here embraces the same price dynamics as would data on the share of shoppers.

The above case study and the specific features of the electricity market provide the reason for choosing the Rosenthal model as a basis for the theoretical approach that defines what variables to include in the econometric model. That is, to analyze if consumer participation, market price, and number of firms offering the specific types of standard electricity contracts are reflected in price dispersion. However, the non-stationary nature of the data claim that the relationship among the variables may be analyzed by a cointegration framework. From analyzing the long run relationship among the variables stemming from the theoretical model, effects between the variables can be identified in the long run.

# 7 Empirical approach

The non-stationary nature of the data[8] in the sample requires careful handling to address variables representing switch volume, electricity contract price data, market price data, and number of firms. Here a cointegration framework for estimation, inference, and interpretation is chosen to treat variables that are not covariance stationary and to indicate the economic relationships among the variables focusing on long run relationships. Following Granger and Swanson (1997), once variables have been classified as integrated of order 1, 2 or 3 ($I(0), I(1)$ or $I(2)$) through the rank test, it is possible to set up models that lead to stationary relationships among the variables. Here a vector error correction model (VECM) is chosen for this purpose.

## The econometric model

This section presents a four equation vector auto regression VAR framework used to quantify the effect on switching, price adjustments and number of firms as outlined by the theoretical relationship in (1) and (2). The models are set up to estimate the presence of long-run relationships among the variables outlined in the theoretical approach, where switch volume, market price and/or forward prices[9] and number of firms are included as variables to rationalize dispersion in prices for the different contract prices.

[8]The data on electricity prices and system price are transformed from weekly to quarterly averages due to the quarterly nature of the switch data obtained from NVE.

[9]In order to capture that retailers choose to manage risk from market uncertainty in fixed price contracts, two systems are estimated for the fixed price 1-year contract; one that includes the system price $(sy_t)$ and another that includes the

With available data on system price $sy_t$, forward price (1 and 3 years) $fwd_t$, switch $sw_t$, and price dispersion[10], $pd_t$ in the three standardized contract segments, and the number of firms offering active contracts in a specific week[11], a VAR model given in equation 3, is set up to comprise the multiple time series for each contract type. In equation 4, the VAR-model is reformulated to a vector error correction model (VECM) according to Johansen (1988). Which is a necessarily step in order to overcome the problem of non-stationary error terms that will lead to non-consistent long-run estimation results, given that the variables are cointegrated in the VAR-model. In the VECM the long-run relationship among the variables, thus having a linear relationship) are estimated by Johansen's maximum likelihood framework.

The basic model of the system expressed as a VAR model with k lags follows:

$$Y_t = \Pi_0 + \Pi_1 Y_{t-1} + ... + \Pi_k Y_{t-k} + \varepsilon_t \tag{3}$$

In equation 3 a vector of variables is modeled as depending on their own lags expressed by $Y_{t-1}$ and on the lags of every other variable in the vector. $\Pi_0$ is a vector of intercept terms and each of $\Pi_1$ to $\Pi_k$ is a 4×4 matrix of coefficients.

Although equation 3 may be differenced to a *I(0)* to overcome the non-stationary nature of the data, we lose long run information due to non-consistent error terms that are *I(1)* in the VAR-model. By reformulating equation 3 to an error correction model (VECM) both the short run and the long run relationship can be estimated jointly if the variables are cointegrated. Hence, the error term will become *I(0)* and consistent also in the long run. Having a multivariate system of variables, this study applies the VECM for estimation of the variables in the system. Even though cointegration measures comovements and not causality, long-run adjustment may thus be assessed through the $\alpha$ coefficients in combination with $\beta' Y_t$. Hence, the $\alpha$ and $\beta' Y_t$ are not idenitified, but the system of where the coefficients represent vectors that forces the system back to equilibrium are. The non-stationary time series in $Y_t$ are cointegrated if there is a linear combination of them that is stationary or $I(0)$ as can be identified in the Johansen's unrestricted cointegration rank test derived from the error correction model.

To obtain a VECM equation (5) is reformulated according to Johansen (1988), such that:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + ... + \Gamma_{k-1} \Delta Y_{t-k+1} + \alpha \tilde{\beta}' \tilde{Y}_{t-1} + \gamma_0 + \gamma_1 t + \varepsilon_t \tag{4}$$

where $Y_t = [pd_t, sw_t, n_t, sy_t{}^{12}.]$ is a vector containing the variables of price dispersion, switch numbers, number of firms, and electricity prices by contract type.

forward price $(fwd_t)$.

[10]Dispersion in prices is expressed as the distance between the highest and lowest prices in the sample at a given time

[11]Week data are reformulated to quarterly data for the estimation

[12]Or alternatively forward price $fw_t$

$\tilde{\beta}' = [\beta, \beta_0, \beta_1]$ denotes a matrix comprising the cointegrating vectors stemming from the long-run parameters $\tilde{Y}_{t-1}$ is a vector of lagged terms representing the system of variables[13]. The $\alpha$ denotes a vector of adjustment parameters to equilibrium in the long-run. The terms $\gamma_0$ and $\gamma_1 t$ denote a constant and a trend parameter[14].

The existence of a cointegrating relationship between the variables in the system enables an estimation of the long-run structure of the $\beta$ vectors and $\alpha$ vectors in each of the cointegrated relations reported in table 1. The estimated $\beta$ values show how much of the adjustments in switch, number of firms, and price are reflected in the dispersion of prices when normalizing on $pd$, while the estimated $\alpha$ value reports an indication of the speed of adjustment to equilibrium. This paper focuses on the long-run relationships to evaluate the system that drives price development over time. Thus, how the variables in the system affects price dispersion in the different contract segments.

The lag length was set to $k = 1$ for all models representing the standard contracts, providing the most parsimonious well-specified VAR-model.

The next section presents the trace tests using Johansen's method for cointegration to identify the existence of a linear combination of the variables i.e. testing for reduced rank. For the reasons already defined, a linear combination of variables is a crucial premise for using the VECM-estimation approach. Estimation results that reveal the long-run relationship of the models and their inherent dynamics of the systems are presented in the next section. The static nature of the theoretical model in (1) and (2) and the nature of the research questions referring to convergence toward a single price equilibrium, limit the estimation to looking at only reduced-form parameters. Any short-run dynamics are outside the scope of this study.

With regard to tests performed on the cointegrated equations of the long-run equations, the series return to zero and the long-run equilibrium rapidly and seem to be stationary and represent the long run relationship of the data. Results are included in Appendix B.

[13] $\tilde{Y}_{t-1} = [Y_{t-1}, 1, t]'$, $\tilde{\varepsilon_t}\,\tilde{}\,N(0, \Omega)$ for $t = 1, ..., T$ and $Y_{-1}, Y_0$ is given.

[14] Due to a restricted trend in the model, $\gamma_{1t}$ is set equal to 0, which indicates that the trend is restricted to being in the cointegration relationship in order to avoid quadratic trends. As shown in Rahbek et al. (1999), we need a restricted linear trend in order to allow for linear trends in all linear combinations of $Y_t$.

# 8 Findings: Existence of long-run relations and their inherent nature

### Trace test and cointegration rank

A first and essential step prior to estimation of the VECM-model is to test for any stationary relationships/linear combinations (cointegration relationship) between the variables in the system. This is done following the approach first presented in Johansen (1988). The null of no cointegration relationships between the variables in the system are evaluated from the two test statistics obtained from respectively the trace tests and eigenvalue test. Results which can be seen in Appendix B support rejection of the null (no linear combination exists) for all contracts. Table 3 in Appendix B shows the eigenvalues of the models and the trace test evaluated against the critical values determined by the sample size of cointegration rank for each contract segment. More specifically, test results suggest a cointegration rank of 1 for the market price contract, the standard variable contract, and for both versions of 1-year fixed price contracts. This implies that a linear combination of these variables is an $I(0)$ process as which a long-run dynamics can be estimated by a CVAR-estimation.

The next section presents the empirical application of the VECM as to estimate the parameters in the system of each model representing a standard electricity contract. Based on these estimates the long-run development in price dispersion for the standardized contracts can be evaluated from the perspective of the variables in the system. Thus, from switching, system price, and number of retailers offering a specific contract as to gain new empirical insight on price development in a mature electricity retail market.

### Long-run structure of models

Table 1 reports the long-run structure of the Cointegrated VAR model (CVAR) after normalizing on $pd$ by setting restrictions on the $\beta$-vector . Column 1 refers the estimation results for model representing the standard variable contract. Standard errors are in parenthesis below the coefficient estimates. Column 2 refers to the results from the model representing the market price contract. Whereas columns 3 and 4 refer to the results for the the fixed 1-year electricity contracts model, respectively including market price and forward price. The $\alpha$-matrix refers to the speed of adjustment of the cointegrated relations; i.e. the "short-run" deviations around the long-run equilibrium. These forces are included to indicate the speed of adjustment of models in the short run.

In summary, results are very much in line with the theoretical framework presented in Section 6; switch has a negative effect on price dispersion for all models, whilst system price or forward price is not significant on price dispersion. The most striking result is that the number of firms have a positive effect on price dispersion for all contracts. Most highly significant for the market price contract. Thus, more firms will be reflected in higher dispersion in prices.

Table 1: Estimated long run structure of C-VAR-models representing the standardized electricity contracts

| | **Std.variable** | **Market. price** | **Fixed 1 yr (market)** | **Fixed 1 yr (forward)** |
|---|---|---|---|---|
| | $\beta$ | $\beta$ | $\beta$ | $\beta$ |
| price dispersion | 1 | 1 | 1 | 1 |
| switch | $\underset{(0.054)}{0.185}$ | $\underset{(0.005)}{0.019}$ | $\underset{(0.023)}{0.098}$ | $\underset{(0.024)}{0.104}$ |
| price | $\underset{(0.111)}{-0.039}$ | $\underset{(0.009)}{-0.007}$ | $\underset{(0.048)}{-0.004}$ | $\underset{(0.038)}{-0.0005}$ |
| firms | $\underset{(0.997)}{-2.457}$ | $\underset{(0.042)}{-0.153}$ | $\underset{(0.182)}{-0.404}$ | $\underset{(0.183)}{-0.413}$ |
| trend | $\underset{(0.123)}{-0.579}$ | $\underset{(0.009)}{-0.052}$ | $\underset{(0.036)}{-0.160}$ | $\underset{(0.034)}{-0.161}$ |
| | $\alpha$ | $\alpha$ | $\alpha$ | $\alpha$ |
| price dispersion | $\underset{(0.130)}{-0.835}$ | $\underset{(0.166)}{-0.522}$ | $\underset{(0.120)}{-0.629}$ | $\underset{(0.118)}{-0.610}$ |
| switch | $\underset{(0.317)}{-0.930}$ | $\underset{(4.316)}{-15.193}$ | $\underset{(0.852)}{-2.854}$ | $\underset{(0.830)}{-2.860}$ |
| price | $\underset{(0.161)}{0.076}$ | $\underset{(2.272)}{-0.732}$ | $\underset{(0.441)}{-0.346}$ | $\underset{(0.518)}{-0.448}$ |
| firms | $\underset{(0.015)}{-0.017}$ | $\underset{(0.379)}{-0.297}$ | $\underset{(0.065)}{0.164}$ | $\underset{(0.568)}{0.165}$ |

Equations 5 to 8 show the estimated long-run structure for the four models representing the standardized electricity contracts, which include the estimated $\beta$-coefficients and their corresponding values and the trend parameters. Note that all equations are level-level; i.e. an increase or decrease in any of the right-hand variables by one unit[15] will increase/decrease dispersion by the coefficient value. For example indicate how adjustments in the number of firms offering a contract will be reflected in dispersion for that specific contract segment.

$$pd - std.var_t = \underset{(0.054)}{-0.185 sw_{t-1}} \underset{(0.111)}{-0.039 mp_{t-1}} \underset{(0.997)}{+2.457 n_{t-1}} + \underset{(0.123)}{0.579 tr} \tag{5}$$

$$pd - marketprice+_t = \underset{(0.005)}{-0.019 sw_{t-1}} \underset{(0.009)}{-0.007 mp_{t-1}} \underset{(0.042)}{+0.153 n_{t-1}} + \underset{(0.009)}{0.052 tr} \tag{6}$$

[15]For switch one unit is equal to 1000 switches du to a better numerical balance.

$$pd - fixed1yr_{mp,t} = \underset{(0.023)}{-0.098} sw_{t-1} \underset{(0.048)}{-0.0044} mp_{t-1} \underset{(0.181)}{+0.404} n_{t-1} + \underset{(0.034)}{0.161} tr \tag{7}$$

$$pd - fixed1yr_{fw1,t} = \underset{(0.024)}{-0.104} sw_{t-1} - \underset{(0.038)}{-0.0005} fw_{t-1} + \underset{(0.183)}{0.413} n_{t-1} + \underset{(0.034)}{0.161} tr \tag{8}$$

From the descriptive approach in Section 5, the hypothesis that contract prices converge to a single price equilibrium is rejected. Here the estimated $\beta-$ and $\alpha$-values add information on factors that are potential sources of dispersed prices. Hence, indicating whether the hypothesis of no relationship between switching, number of firms and market price on dispersed prices can be rejected.

The results from the variable price model in Equation (5) suggest that price fluctuations in the underlying market price has no significant effect on dispersion in contract prices. However, the estimates for the other variables in the model return significant results. First, switch volume seem to have a significant effect on dispersion in prices for this contract. Thus, an increase by 1000 switches decrease dispersion in prices by 0.19 øre/kWh. Secondly, entering of more firms that offer variable price contracts at the price comparison site seem to increase dispersion in prices by an estimated amount of 2.45 øre/kWh. These results indicate that movements of consumers will affect price spread for this contract and that the price range seem to increase as more firms offer this specific contract at the price comparison site.

Results from estimation of the market price model in Equation (6) return moreover the same results. Although with a highly significant result from entering of more firms on dispersion in prices indicating that more contracts seem to increase price spread. Increased switch numbers reduce dispersion in prices, however with a lower magnitude than in the variable price contract. Here an increase by 1000 switches is estimated to reduce dispersion in standardized spot price contracts by 0.019 øre/kWh. Whereas one more firm will increase dispersion by 0.15 øre/kWh.

For the fixed price contract in (8) and (7) results return a uniform pattern across models. Thus, *switch* and *number of firms* seem to affect price dispersion in these contracts in the long run. The estimated coefficients for the 1-year fixed price contract return more or less similar results. $Price$ is not significant in any of the models, while $switch$ has a significant effect on dispersion. For both contracts an increase by 1000 switches reduces dispersion by approximately 0.1 øre/kWh. It is no surprise that altering of the market price is of marginal importance du to the rigid characteristics of this contract. Thus, in which the supplier has limited opportunities to change the price during a contract period. In addition, the stable price structure is such that any price increase will first come as a result of many small price adjustments over some period. A marginal price adjustment is therefore not likely to have any significant effect on dispersion in prices. Furthermore, results for both fixed price models return positive and significant results for number of firms. Hence, as a new firm enter dispersion in fixed price contracts are suggested to increase by 0.40 øre/kWh.

Based on these results, the hypothesis of no significant relationship between switch numbers and number of firms offering a specific contract price on spread in electricity prices is rejected. However, price level does not seem to have any significant effects on dispersion.

Results from the $\alpha$-matrix show the adjustment coefficients for the short-run equilibrium around the long-run equilibrium. In general large (close to -1) negative $\alpha$-values indicate that the short run deviation around the long-run equilibrium return to equilibrium fast and that models are well-specified. Here $\alpha$-values are negative for all values except for number of firms $n_{t-1}$ in the one-year fixed price contracts. Thus, this can indicate that if there is any disequilibrium in the market for fixed-price contracts, more firms may enter as to seek opportunities in the market.

The trend parameter is significant through Equations (5) - (8). The modest values of the trend parameter indicate a good fit for the model. However, a significant trend, although modest, may suggest that there are factors outside the model that are important in keeping prices from converging to a single price equilibrium. The rigid nature of the dispersion in prices seen in the estimated $\alpha$-values may support this. In other words, an alternative hypothesis to rationalize dispersion in prices, such as equilibrium in mixed strategies, which retailers randomize prices to attract shoppers and maintain margins on loyals, may be a plausible hypothesis to explain some of the dispersion in prices. However, this is outside the scope of this paper and is left for future studies.

## 9 Final considerations and concluding remarks

This paper explores price dispersion using a twofold approach. First, the paper presents descriptive statistics and demonstrates that prices for standardized electricity contracts do not converge to a single price equilibrium. Next, the paper investigates and estimates if consumer switching, adjustments in electricity market price, and number of firms, are reflected in dispersion in contract prices in the long run. Such long-run dynamics have not received much attention in the literature. Thus, this study provides new empirical insights in price development in electricity contracts from one of the first electricity electricity sectors to undergo liberalization.

Results indicate that having a segment of consumers that do not switch to the best deal, leave retailers with pricing decisions that are a best response to this switch behavior. Thus, some contracts within a specific contract segment are high price, others are low price. This finding is in line with general theory on price dispersion and in line with previous studies exploring market outcomes in similar markets; Simshauser and Whish-Wilson (2017), Gugler et al. (2018), Nelson et al. (2018), Mulder and Willems (2019).

By examining the long-run relations, a more striking result is that the entry of more retailers offering nationwide standardized contracts seems to strengthen price dispersion across all contract segments. This is strongly significant in the market price contract, and may indicate market power. Entrants of new firms and contracts seem to have a negative effect on competition. Thus, prices get more dispersed as more retailers and contracts enter.

These market dynamics can be explained with help of consumers´ information issue as there are more contracts to choose from. Measures that contribute to better information about the contracts make it easier to change electricity supplier for all customers. This will limit the opportunities for retailers to price discriminate by offering a wide portfolio of contracts.

In addition, results indicate that the included $trend$ component is statistically significant and positive. This suggests that there are potential effects on price dispersion caused by factors not specifically included in the model. Looking beyond this study, one possible explanation may be mixed price strategies or the existence of some kind of market power; for example tacit collusion. As the market is maturing there may be a "settling" into roles as price leaders, market share hunters or nurturing a small group of loyals.

This highlights the importance of looking beyond the seemingly well functioning market to correct for and gather new and more sophisticated insights into potential sources of market imperfections, so that these can be targeted with the most effective policy measures to facilitate an efficient expansion of the sector in the long run.

# A Summary statistics

Table 2: The data series and their descriptive statistics

| Data | Unit | Obs. | Mean | Std.dev. | Min | Max |
|---|---|---|---|---|---|---|
| Spread std. var contract | øre/kWh | 48 | 11.37 | 7.40 | 4.20 | 42.98 |
| Spread mrk price plus contract | øre/kWh | 48 | 3.05 | 1.04 | 1.44 | 5.07 |
| Spread fixed 1 yr contract | øre/kWh | 48 | 5.48 | 2.71 | 0.85 | 12.00 |
| Spread fixed 3 yr contract | øre/kWh | 48 | 2.16 | 1.70 | 0.01 | 7.04 |
| Switch of service provider (in 1000) | counts | 48 | 64.84 | 19.96 | 21.4 | 113.9 |
| Market price electricity | NOK/kWh | 48 | 29.45 | 9.43 | 8.52 | 51.46 |
| Forward price 1 month | øre/kWh | 48 | 38.04 | 11.55 | 17.27 | 67.09 |
| Forward price 3 month | øre/kWh | 48 | 39.45 | 11.22 | 19.56 | 67.81 |

# B Trace test, cointegration rank, and predicted cointegrated equations

Figure 9 shows a panel with the specifications of the cointegrating equations for the long-run equations of the standardized contracts. The plots support the idea that the cointegrated equations are stationary such that a linear combination of the variables is $I(0)$. Furthermore, all processes, as shown in Figure 9, return to zero relatively quickly, which indicates smaller persistence in the models. That is an indication that the estimated $\alpha$-values for the long-run dynamics are likely to be negative and significant something also found in our estimates.

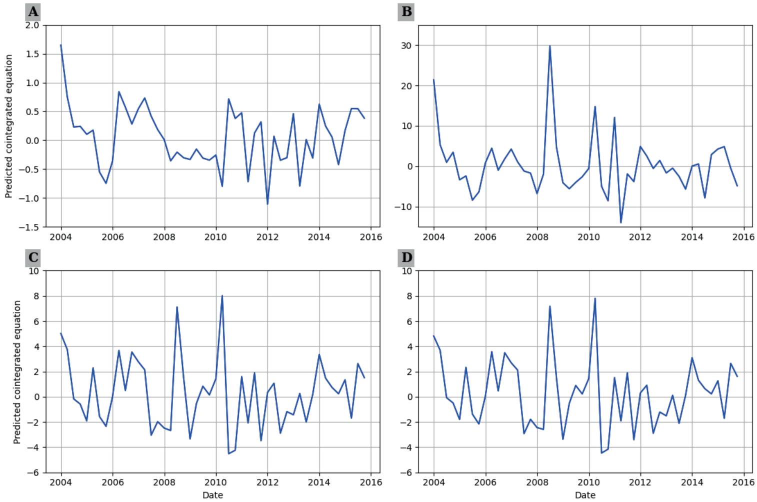


Figure 9: The predicted cointegrated equations for the standardized contracts graphed over time as to check for stationary relations.

A significance level of 1% suggest r=1 for all models. Eigenvalues of model and trace test of cointegrated rank in standard electricity contracts are shown in Table 3, where stars $*$ define rank level.

Table 3: Eigenvalues of model and trace test of cointegrated rank in standard electricity contracts

| rank | parms | log-likelihood | eigenvalue | trace stat. | 5 % critical. val. | 1 % critical value |
|---|---|---|---|---|---|---|
| | Std var. contract | | | | | |
| 0 | 8 | -578.364 | | 77.165 | 54.64 | 61.21 |
| 1 | 15 | -558.427 | 0.572 | 37.291 * | 34.55 | 40.49 |
| 2 | 20 | -549.477 | 0.317 | 19.391 | 18.17 | 23.46 |
| 3 | 23 | -542.199 | 0.266 | 4.83 | 3.74 | 6.4 |
| 4 | 24 | -539.781 | 0.098 | | | |
| | Market price contract | | | | | |
| 0 | 8 | -476.106 | | 71.178 | 54.64 | 61.21 |
| 1 | 15 | -460.103 | 0.493 | 39.172 * | 34.55 | 40.49 |
| 2 | 20 | -450.079 | 0.347 | 19.125 | 18.17 | 23.46 |
| 3 | 23 | -443.967 | 0.229 | 6.90 | 3.74 | 6.4 |
| 4 | 24 | -440.517 | 0.136 | | | |
| | 1-year fixed -system price | | | | | |
| 0 | 8 | -543.009 | 0.506 | 63.845 | 54.64 | 61.21 |
| 1 | 15 | -526.422 | 0.313 | 30.670* | 34.55 | 40.49 |
| 2 | 20 | -517.590 | 0.164 | 13.006 | 18.17 | 23.46 |
| 3 | 23 | -513.382 | 0.093 | 4.590 | 3.74 | 6.4 |
| 4 | 24 | -511.087 | | | | |
| | 1-year fixed -fwd price | | | | | |
| 0 | 8 | -553.344 | 0.505 | 67.961 | 54.64 | 61.21 |
| 1 | 15 | -536.828 | 0.340 | 34.929* | 34.55 | 40.49 |
| 2 | 20 | -527.068 | 0.207 | 15.408 | 18.17 | 23.46 |
| 3 | 23 | -521.617 | 0.091 | 4.506 | 3.74 | 6.4 |
| 4 | 24 | -519.364 | | | | |

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# Paper IV

# Price Leadership and Electricity Retailing

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August 30, 2021

**Abstract**

In this paper we estimate a Markov chain model of price changes as to learn about pricing strategies in the Norwegian electricity retail market using weekly data. By assessing descriptive statistics and estimation results we disentangle observations and assign retailers different motivations for price adjustments. We find patterns indicating that specific retailers possess positions as price leaders and that differences in margin sensitivity for price changes are extensive. Hence, our results add to the suspicion that accurate and timely information about prices and announced dates for price adjustments seem to facilitate such pricing strategies. In addition, the results indicate that there is a "dark side" of price transparency to this market.

**Keywords:** Electricity markets, Electricity retailing, Price leadership, Pricing strategies, Market transparency, Hidden Markov models.

**JEL:** C24, D40, D47, L11, Q41.

## 1 Introduction

Norway restructured the electricity sector by The Energy Act of 1991 with an overarching aim to improve sector efficiency in the long run. Two essential elements in this regard were establishment of markets for electricity and introduction of common carriage principles to the network system. Industrial consumers participated in the new wholesale market from the outset. Retail competition for household consumers was not effective until a few years later when systems for efficient metering and billing were in place and fees associated with switching retailer had been eliminated. In an attempt to further encourage retail competition and increase consumer mobility

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retailers were required to report electricity contract prices to an interactive Internet site operated by the Norwegian Competition Authority (NCA). This site provided up-to-date information about current and planned prices and fees from all retailers, and thus giving customers easy and transparent access to comparable and reliable price information.

At the same time, the NCA web site provided all retailers with accurate and timely information about the pricing behavior of all other retailers. Stigler (1964) argues that increased transparency in information might have an adverse effect on the competitiveness of a market. Transparency in prices enables firms to observe and hence coordinate prices at a higher level than what would prevail in a competitive market. A similar argument is made by von der Fehr (2013) in the context of electricity markets: more information can potentially facilitate behavior that undermines competition and results in market outcomes that are characterized by collusion rather than competition.

Our focus is on the “dark side” of price transparency in the electricity retail market, that is, if availability of detailed and timely price information can serve as a facilitating tool for price coordination among retailers.

Collusive behavior, either explicit or tacit, enables retailers to raise prices above the competitive equilibrium and thus obtain above normal profits. Tacit collusion occurs when firms are able to reach an agreement, or common understanding, of coordinated prices simply by observing each others pricing behavior Motta (2004).

The retail market have several features which Ivaldi et al. (2003) consider important to increase the likelihood of collusion; a fairly low number of firms, equal marginal costs (the wholesale electricity market price), the demand side is highly inelastic, the technology is mature and stable (with no firm having technical advantages), and electricity is a homogeneous good with very limited options for product differentiation. That said, one perspective which challenges the view of electricity as a "pure" homogeneous good is that of "packaging" electricity into different contracts due to risk preferences and volatility of prices Fange (2021b). Thus, from this perspective one may argue that electricity contracts can be considered as slightly heterogeneous products distinguished by consumers’ risk preferences. From this perspective one may argue that electricity *contracts* can be considered as slightly heterogeneous products distinguished by consumers’ risk preferences. However, within a price contract segment electricity is a homogeneous product.

Keeping in view the above discussion, this paper explores whether there are any empirical traces and findings that resembles use of the official price comparison site as a price coordinating tool. Using weekly data on specific contract prices reported to NCA from week 2 in 2005 to week 52 in 2009 we pursue to gain new insight to retailers pricing behavior by answering the following questions:

1. Do retailers mimic and follow price adjustments made by others?
2. Are there any price leaders in this market?

As will be clear below, this paper answers these questions from the perspective of nationwide and prominent regional retailers comprising consistent data on contract prices under the period of study.

The paper proceeds as follows. Section 2 gives an overview of related literature on price transparency and price leadership, while we lay out the Markov chain model of price changes in Section 3. Section 4 presents the Data. Section 5 provides discussion of results while Section 6 concludes.

## 2 Electricity Retail Markets

The question of potential tacit collusion among retailers has remained essentially unanswered for restructured electricity markets. A few years after the Norwegian electricity market commenced several studies evaluated the general market performance from a comparative and structural perspective (Amundsen and Bergman, 2003; Johnsen, 2003; Bye et al., 2003; Amundsen et al., 2006; Littlechild, 2006; Olsen et al., 2006). These studies, in general, argue that the overall structural setup of the market has been a success. Bye et al. (2003), however, point to the dark side of transparency and argue that a transparent market (such as the Norwegian electricity market) may be vulnerable to collusive market behavior and hence higher prices.

### 2.1 Price transparency and colluding behavior

A considerable body of literature investigates whether transparency in prices leads to an increased likelihood of collusion. An important early study in this regard is Albæk et al. (1997). The essential finding in this study is that following intervention by the competition authorities to gather and publish prices for cement, prices increased on average between 15-20 percent. The study argues that the change in information structure allowed firms to reduce the intensity of competition and as a result prices increased.

The study by Georgantzìs and Sabater-Grande (2002) explores how the eight largest manufacturers of agricultural tractors in the UK were accused by the Commission of the EC for anti-competitive practices in light of price coordination through the UK Agricultural Registration Exchange. The study propose that market transparency in non price data (as accused by the European Commission) may be a collusion facilitating device to establish stability in otherwise unstable cartels.

In a study of the market for medical devices in the US, Hahn et al. (2008) argue that increased transparency in prices for medical devices increases consumer costs in this industry. Whereupon the study argues that specific market features for the medical industry make it prone to colluding behavior. The study emphasize repeated interaction, limitations on substitution and inelastic demand, large seller concentration, and specialized products as important factors.

In the US price coordination through a price overview board has previously been the subject of a civil antitrust suit under section 4 of the Sherman Act in order to prevent and restrain violations of section 1 by eight major air carriers US Department of Justice (1994). DOJ accused the air carriers to fix prices on domestic airline routes in the US through their joint venture Airline Tariff Publishing Company (ATP). DOJ further alleged that the airlines used ATP to conspire and exchange information to increase prices. The final judgment agreed to by ATP and the accused airlines involved commitments and certain limitations on advertising of price fares and any first ticket dates and last ticket dates, fares or any other information on proposed changes in fares. That is, severe limitations on extended information of forthcoming price adjustments.

From this review, we infer that price transparency and extended information on price adjustments might function as an option for retailers to observe and adjust their pricing behavior, thus increasing the likelihood of collusion. The next section outlines the analytically framework setting the stage for the study.

## 2.2 Price Leadership

Both price transparency and dynamic interaction among retailers are well established features of the electricity retail market. That is, the presence of a price comparison site provides easy, accurate and "real-time" price information in a market where retailers interact continuously by vying the same customers and using the web site to assess their price offers.

One potential facilitating practice for tacit collusion is that of price leadership. Price leadership occurs if one firm initiates a price adjustments and it is then immediately followed by other firms in that market (Stigler, 1947; Markham, 1951; Lanzillotti, 1957). Scherer (1970) classifies price leadership into three main types: dominant, collusive and barometric. Dominant price leadership occurs if the firm is defined, or viewed, as the largest, say, based on market share, establishes a leading price with the other firms following suit with matching price changes. Collusive price leadership refers to a case where a principal firm set prices which are followed by the other firms. Price changes under a collusive price leadership should be rather infrequent. Under barometric price leadership, the price is set around the competitive level. A barometric price leader is viewed by the other firms as being better informed. Thus, the barometric leader does not have to be dominant as measured by market share or market position. A barometric price leader remains a price leader only as long as the firm is able to interpret market signals better than other firms.

In a market for a homogeneous product such as electricity price changes should reflect changes in the margin of the product. However, empirical studies find that rapid price changes due to changes in margin size are not always the case. For example the study by Mirza and Bergland (2012) of the Norwegian electricity market find that margin squeezes are quickly followed by price increases while downward price adjustments are slower to follow. Tappata (2009) analyzes markets comprising competitive firms and rational, but partly informed, consumers and find that prices tend to be more sticky downwards than upwards.

If any form of price leadership exists in the electricity retail market we would expect to observe certain systematic temporal patterns of price changes. In a market characterized by barometric price leadership the leading firm would react quickly, and correctly, to margin changes and other firms would follow shortly afterwards. On the other hand, in a market characterized by strategic price leadership a price leader would increase prices without necessarily being squeezed at the margin with other firms following any price adjustment at a later date. If another firm appears to be the leader for downward price adjustments this would be stronger evidence for strategic price leadership compared to barometric price leadership.

Different price leadership types and their features can be summarized as:

1. Barometric price leader: margins are important, and other firms tend to follow.
2. Strategic price leader: margins are not always important, other firms tend to follow.
3. Price follower: follows the price leaders (barometric or strategic) with similar price changes.
4. Competitive pricing: margins are important, and a firm is sometimes a price leader, sometimes a price follower.

## 2.3 A Markov Chain Model of Price Changes

The pricing strategies firms follow are not known nor directly observable. Only actual price changes are observed. We propose to use a hidden Markov chain model to model the pricing behavior of electricity retailers where hidden states represents the firms' pricing strategies. Hidden Markov models are widely used in speech recognition and machine learning (Rabiner, 1989; Murphy, 2012), but also in time-series econometrics (Hamilton, 1989, 1990), electricity price forecasting González et al. (2005), and in industrial organization (Ellison, 1994; Fabra and Toro, 2005; Noel, 2007; Hyytinen et al., 2018). The input-output hidden Markov model (IOHMM) generalizes the static Markov chain transition probabilities to time-varying transition probabilities depending upon a vector of observable variables (Hamilton, 1989; Diebold et al., 1994; Bengio and Frasconi, 1995). This generalization is important as it allows state transition probabilities to depend upon price margins and past pricing behavior.

Let a retailer charge price $p_t$ at time $t$. The retailer must then decide the price to charge in the next period, $p_{t+1} = p_t + y_t$, where $y_t$ is the price change. The price can remain unchanged ($y_t = 0$), increase ($y_t > 0$) or decrease ($y_t < 0$). Depending on the competitive nature of the market and the retailer's position in the market the retailer can employ different pricing strategies.

The unobserved pricing strategy of a retailer is a sequence of hidden states where each state represents the motivations for a pricing decision. The hidden state $S_t$ at time $t$ is drawn from a finite set of states indexed by the set $\mathcal{S}$. Transitions between states over time are governed by a Markov chain with time-varying state transition probabilities:

$$\pi_t^{s,r} = \Pr(S_{t+1} = r | S_t = s, z_t) \tag{1}$$

where the probability of moving from state $s$ in one period to state $r$ in the next period depends not only on the state $s$, but also a covariate vector $z_t$. Conditional on the motivation in state $s$ and influencing factors, denoted $x_t$, the probability of observable price change $y_t$ is

$$\ell_t^s(y_t) = \Pr(y_t | S_t = s, x_t). \tag{2}$$

This equation defines a switching regression model for the observed price changes with the time-varying Markov chain governing the transition probabilities.

Figure 1 shows the IOHMM and illustrates the interconnected time dimensions of the model. The transition probabilities from equation (1) takes the Markov chain from one point in time to another. The switching regressions, conditional on the state, generate the observed price change $y_t$ and also the likelihood of observing that price change given the state and covariates, i.e. equation (2).

These two equations jointly defines a stochastic model of price changes over time where the price changes depends both on the unobserved pricing strategy and the history of price changes in the market. The next section provides a detailed description of an empirical specification of this model.

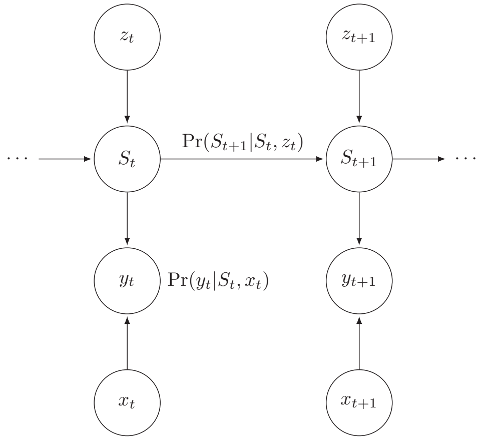


Figure 1: The interconnected dimensions in the Input-Output Hidden Markov model.

## 3 Empirical framework

Following our discussion of price leadership we hypothesize that a retailer faces five different options for adjusting the current contract price as outlined in Figure 2. Price increases and decreases can each be realized through two options: i) a price adjustment immediately following a similar price adjustment by other retailers, or ii) as a response to changes in the margin caused by, say, changes in the underlying wholesale price. The no change option serves as a baseline from which price changes are evaluated with respect to different models of price leadership. The transition probabilities out of one state to a state in the next period are modeled as multinominal logit models. The statistical significance, or insignificance, of the time-varying factors in the multinominal logit models enables discrimination between the different models of price leadership.

The full IOHMM encompassing the Markov chain, the state transition probability models and the switching regression models, can be jointly estimated using the Baum-Welch variant of the EM algorithm taking into account the time-varying transition probabilities (Diebold et al., 1994; Bengio and Frasconi, 1995). The state transition probabilities are estimated as separate multinominal logit models for each state (Wooldridge, 2010). We use observed price changes to specify separate Tobit models (Hayashi, 2000; Wooldridge, 2010) for positive and negative price changes as well as a specialized no change state when the price does not change [1]

[1] As this model is not a standard IOHMM the estimation is utilizing an adapted version of the Python code developed by Bergland et al. (2021) for estimation of IOHMM with switching regression models specified as Tobit models.

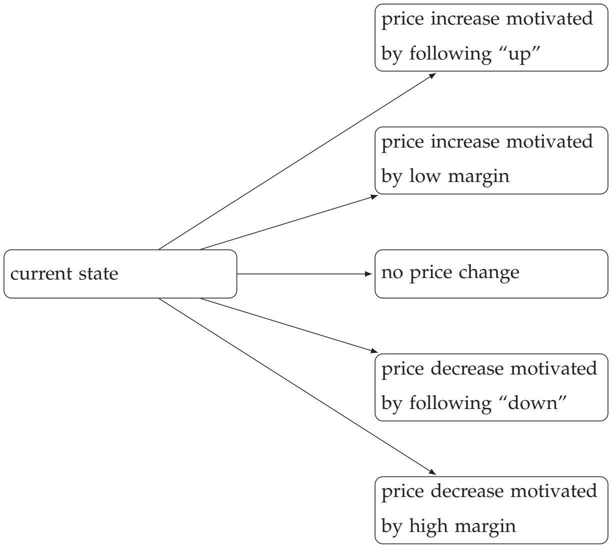


Figure 2: Pricing options

The EM algorithm is an iterative estimation procedure that cycles through an expectation (E) step and a maximization (M) step until parameter estimates converges. The E-step estimates the latent parameters of the hidden Markov chain, that is the expected (predicted) state transition probabilities, $\hat{\pi}^t_{sr}$, and the marginal state probabilities, $\hat{\pi}^t_s$, i.e. the expected probability of being in state $s$ at time $t$ given the observed data. The M-step utilizes the estimates of the latent variables as data in a maximum likelihood estimation procedure for the switching regressions and the state transition probabilities. The marginal state probabilities $\hat{\pi}^t_s$ serves as weights in a weighted maximum likelihood estimator for each switching Tobit regression model. The resulting estimates for the likelihood, $\hat{\pi}^t_s$, of observation $t$ in the model for state $s$ serves as observational likelihoods in the E-step. The state transition probabilities $\hat{\pi}^t_{sr}$ are used as observed outcome probabilities in a multinominal logit model for each state $s$. The predicted probabilities from the multinominal logit models serves as time-varying state transition probabilities in the next iteration of the E-step.

From the multinominal logit model we calculate the average partial effect (APE) (Wooldridge, 2010) of market price on the state transition probabilities. The APEs can be used to identify states where the effect on transition probabilities into the states are uniformly either positive or negative and statistically significant. Positive price adjustments are drawn from a finite set of states $S = \{s_1, s_2\}$, and negative price adjustments are drawn from a finite set of states $S = \{s_{-1}, s_{-2}\}$. The uniformly positive and negative values embrace the pricing options related to margin squeeze (size) for up/down and following the market up/down. States identified through this screening process are candidates for further investigation as to distinguish between a price rise from a rise in underlying wholesale price, or mimicking of other retailers price rise. Correspondingly with states associated with a price decrease.

# 4 Data

We are using data from the NCA web site to construct a detailed history of price changes for all retail market participants. The NCA data consists of weekly records with information about the actual price for each retailer in that week. The underlying database have probably gone through multiple incarnations as there are periods where the weekly records include information about the exact time the retailer entered the price information into the NCA system. As retailers are required to give two weeks advance notice of (almost) all price changes this information identifies the time of announcing the price changes. This in turns allows us to construct a detailed time-series of price changes for each retailer. With the two week advance notice requirement using announced prices better describes the pricing dynamics in the market than the actual prices charged.

The resulting history should be accurate with one possible exceptions. If there are more than one price change entered taking effect in the same week only the latest price change would be available to us. We do not have any means to assess how frequently, if at all, this may have happened.[2] The period for which we were able to construct a continuous series with daily price history is 10.01.2005–12.31.2009.[3]

Retailers are offering three different contract types: i) fixed-price contracts for a period of one or three years, ii) a wholesale market price contract with a mark-up, and iii) a variable price contract. The variable price contract was the default contract in the initial stage of the retail competition. The price stated in the contract is fixed, but the retailer can change it at any time as long as the customers are given at least a two week notice. The variable price contracts (the dominant contract form used in the period 2005–2009 (Fange, 2021a)), will be analyzed here.

In addition to the price per kWh of electricity the retailers typically add a fixed monthly charge. Here we follow the common practice as used by NCA at that time to calculate an average price for an annual consumption of 20 000 kWh.

The weekly system price for the Nordic electricity market is obtained from the electricity market operator Nord Pool. The system price is used to calculate the price margin as the ratio of the

[2]There will be no traces in the data if any of the retailers where using the price comparison site for communication along the lines of the ATP case discussed earlier.

[3]There are intermittent periods with time information prior to 2005, but with long gaps. The NCA changed the reporting and design of their website in 2010.

average contract price and the system price. The actual margins for the retailers are not observable and will depend on the retailers' hedging strategies and the existence of any bilateral (long-term) supply contracts. However, for the marginal quantity the retailer is facing the wholesale market where the system price serves as a reference price.

In the period 2005–2009 some 12–16 retailers offered nationwide contracts, with another 60+ retailers offering contracts within a limited geographical area (Fange, 2021a). We are limiting the number of retailers included in the analysis to nationwide and a few regional retailers serving the populous aress in Southern Norway. Due to substantial entry and exit of retailers, several companies qualifying under this definition are left out due to limited number of observations. Retailers with prepaid contracts are excluded from the sample.

Table 1 comprises the summary statistics for announced prices measured in øre/kWh, average rank, and the number of times a specific retailer is ranked first. A few observations stand out; Fortum Markets AS has an average price rank 13 (out of 14) and has never been ranked first. Whereas Haugaland Energi is ranked first 471 times out of 1817 days.

Table 1: Summary statistics of posted retail prices (øre/kWh) and price rankings. $N = 1817$.

| Retailer | Mean | StdDev | Min | Max | Ranks | First |
|---|---|---|---|---|---|---|
| Eidsiva Marked | 43.04 | 13.36 | 21.50 | 77.40 | 10.63 | 9 |
| Fitjar Kraftlag | 41.19 | 13.10 | 22.29 | 77.80 | 8.36 | 43 |
| Fjordkraft | 42.09 | 13.72 | 21.30 | 78.59 | 9.28 | 1 |
| Fortum Markets | 44.87 | 13.49 | 22.88 | 79.38 | 13.00 | 0 |
| Gudbrandsdal Energi | 41.04 | 13.89 | 21.34 | 78.75 | 6.79 | 39 |
| Hafslund Strøm | 41.60 | 13.81 | 21.35 | 77.80 | 8.30 | 59 |
| Haugaland Energi | 39.36 | 13.52 | 21.10 | 78.50 | 5.00 | 471 |
| Luster Energiverk | 41.12 | 13.10 | 21.20 | 74.00 | 7.74 | 14 |
| Lyse | 41.27 | 13.25 | 21.70 | 73.90 | 8.05 | 30 |
| Lærdal Energi | 39.45 | 12.75 | 21.00 | 74.60 | 4.06 | 299 |
| NorgesEnergi | 39.80 | 13.33 | 21.19 | 77.79 | 3.84 | 239 |
| Telinet Energi | 40.85 | 14.12 | 20.95 | 77.95 | 7.07 | 225 |
| Total Energi | 40.18 | 13.63 | 21.40 | 77.78 | 5.36 | 417 |
| Ustekveikja Energi | 41.01 | 13.58 | 21.38 | 77.80 | 6.79 | 3 |

From Table 2 it is evident that Eidsiva Marked has a distinguishable higher total number of price increases compared to other retailers. For price decreases a few retailers (NorgesEnergi, Ustekveikja Energi, Eidsiva Market, and Gudbrandsdal Energi) have a substantial higher number of price adjustments than others. The frequency of price adjustments seem to be correlated (not perfectly) with the size of price adjustment. Thus, frequent price adjustments are small and infrequent adjustments are relatively large. Average price margins included in Table 3 show that Fortum Markets has the highest mean price margin (50.6 %). Furthermore, results show that Haugaland Energi and Lærdal Energi has the lowest price margin (both 31.8 %).

Summary statistics add weight to the earlier suspicion that retailers differ in their pricing behavior. Thus, some retailers seem to interpret market signals early on and adjust prices frequently while others do not. This suspicion is further strengthened when we compare price margins across retailers and observe that average margins differ across the sample.

Table 2: Summary statistics of price increases and decreases (øre/kWh).

| | Price decrease | | | | | Price increase | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Retailer | N | Mean | StdDev | Min | Max | N | Mean | StdDev | Min | Max |
| Eidsiva Marked | 75 | 2.06 | 2.14 | 0.45 | 17.50 | 60 | 2.88 | 2.06 | 0.55 | 12.40 |
| Fitjar Kraftlag | 45 | 3.04 | 2.80 | 0.26 | 16.84 | 31 | 4.89 | 3.63 | 0.75 | 16.19 |
| Fjordkraft | 73 | 1.99 | 1.97 | 0.06 | 14.06 | 48 | 3.40 | 3.65 | 0.69 | 23.90 |
| Fortum Markets | 40 | 3.71 | 2.93 | 1.07 | 16.25 | 33 | 5.01 | 3.58 | 0.95 | 21.31 |
| Gudbrandsdal Energi | 73 | 1.82 | 2.58 | 0.08 | 20.30 | 42 | 3.37 | 4.05 | 0.21 | 24.07 |
| Hafslund Strøm | 62 | 2.42 | 2.08 | 0.10 | 10.10 | 40 | 3.88 | 3.25 | 0.55 | 16.50 |
| Haugaland Energi | 54 | 2.47 | 1.71 | 0.35 | 8.50 | 31 | 4.51 | 3.49 | 0.75 | 12.24 |
| Luster Energiverk | 43 | 2.90 | 2.32 | 0.85 | 13.96 | 30 | 4.44 | 2.52 | 1.04 | 10.60 |
| Lyse | 50 | 2.64 | 2.53 | 0.50 | 17.40 | 34 | 4.26 | 2.81 | 1.20 | 15.20 |
| Lærdal Energi | 58 | 2.11 | 2.35 | 0.10 | 12.10 | 38 | 3.49 | 2.18 | 0.50 | 8.87 |
| NorgesEnergi | 79 | 1.79 | 1.96 | 0.10 | 13.50 | 38 | 3.93 | 3.07 | 0.85 | 18.30 |
| Telinet Energi | 46 | 3.08 | 2.09 | 1.00 | 11.00 | 24 | 6.31 | 5.89 | 2.00 | 26.00 |
| Total Energi | 46 | 3.00 | 2.84 | 0.20 | 11.00 | 31 | 4.77 | 4.79 | 1.10 | 24.08 |
| Ustekveikja Energi | 76 | 1.70 | 2.02 | 0.07 | 14.05 | 36 | 3.94 | 2.54 | 1.08 | 10.90 |

## 5 Estimation results

Once it is establish from the qualitative assessment of descriptive statistics that retailers seem to differ in their pricing behavior, we follow the empirical framework outlined in Section 3 which enables us to evaluate proposed hypothesis as to further explore any traces of collusive behavior in this specific market;

1. First, the Censored (Tobit) regression reveals whether the margin size associated with a negative/positive price change is significant.

2. Next, using the results from the multinomial logit model (MNL) return the APEs of a change in margin on state transition probabilities to other states, uniformly identified as either positive or negative and statistically significant (pricing options as outlined in Figure 2).
3. Eventually, using the IOHMM and the multinominal logit model, results give the predicted average partial effects of a transition from state 0 given the observed data of other retailers price adjustment.

### 5.1 Margin size on price adjustments

The IOHMM model estimates *both* the Tobit model in a switching regression setup *and* the MNL (providing the probabilities for the switching regression). The estimates of the switching Tobit regression models for the magnitude of price changes are reported in Table 4. The price margin is statistically significant at the 5% level for 22 out of 28 coefficients for positive price adjustments and for 16 out of 28 coefficients for negative price adjustments. These results suggest an asymmetry in price changes where adjustments of prices up are closer related to price margins than price decreases. A noticeably result is that Hafslund Strøm has no significant effects

This is in line with the results in Mirza and Bergland (2012) examining the pass-through of wholesale electricity price to the end-user consumers with a variable price contract in Norway. Thus, from these results we conclude that a margin size associated with a negative/positive price adjustments is not uniformly significant. Hence, adding to the suspicion that there are other motivations for price adjustments than margin size.

### 5.2 Adjustment in margin on state transition probabilities

The MNL models of state transition probabilities include both own price margin and the past pricing behavior of the other retailers. The transition probabilities going from the no price change to any other state represents the probability of adjusting price. The testing of statistical significance of margin and/or recent price changes is important for identification of the retailers motivation for the price changes.

Table 4 gives the estimated APE of own price margin on the probability of transition into the different price changes states.

Furthermore, results from the Wald-test support a rejection of the hypothesis of all parameters equal to zero. Thus, we cannot argue that a change in the margin have no effect on the transition probabilities into different states. APE-values for transmission to states 2 and -2 are uniformly significant although APE-values for transmission to states 1 and -1 are not. Thus, entering into pricing states 1 and -1 does not seem to have a uniform association with adjustments in margin size. Thus, this adds to the suspicion that there are other motivations for adjusting prices than margin size. Furthermore, we observe that chi-values vary and that there is a suggestive difference in the estimated APE-values. Thus, results emphasize that retailers exhibiting high APE-values are more prone to switch pricing strategy following an adjustment in margin than others. An important interpretation of the results is that retailers with higher APE-values have a greater increase in the probability of changing their price from a given margin than other retailers. More specifically, results for pricing states -2 and 2 suggest that Gudbrandsdal Energi, Ustekveikja Energi, Fjordkraft and NorgesEnergi are more prone to adjust prices down following an adjuststment in margin. Whereas Eidsiva Marked, Fjordkraft, Hafslund Strøm and Lærdal Energi are more prone to adjust prices up following an adjustment in margin size[4].

Results from the multinomial regression add weight to the earlier suspicion that there are patterns indicating that specific retailers possess positions as price leaders in this market. To follow these indications as to disentangle specific pricing patterns, we need further investigations as to identify how retailers adjust prices in response to other retailers pricing behavior. As will be clear below, that is exactly what the results from the expected partial effects on transition probabilities given the observed data of other retailers allow.

### 5.3 Price adjustments given observed data of other retailers price adjustments

Figures 3 and 4 comprise the significant values of the predicted average partial effects on the transition probabilities from state 0 given the observed data of other retailers price adjustment. Thus, results enable us to identify any pricing dynamics that resembles that of price leadership. Pricing dynamics as displayed in Figures 3 and 4 are disentangled as follows; pricing states 1 and -1 are marked in blue and pricing states 2 and -2 are marked in red. The arrows should be interpreted as follows; a price adjustment initialized by the retailer from which the arrow points from are immediately followed by the retailers pointed at. A comprehensive summary of the estimated results obtained from the IOHMM of price adjustment given observed data of other retailers price adjustments are given in Tables 6 - 19.

Results presented in Figures 3 and 4 suggest four prominent pricing patterns; Eidsiva Marked stands out as a clear price leader for price decreases and NorgesEnergi seem to be an apparent follower for adjustments down. For positive price adjustments Hafslund Strøm seems to be a cognizable price leader for positive price adjustments, whereas Fjordkraft stand out as the most apparent price follower candidate.

More specifically, 5 out of 14 retailers have a significant APE of an immediate price adjustment

[4]Estimation results in Table 3 should be interpreted such that the estimated APE-values corresponds with an adjustment in margin size by 100 øre/kWh increase.

following Eidsiva Market down. Thus, giving rise to the suspicion that these are price follower candidates. In addition, results reveal specific pricing dynamics among certain retailers. Thus, Ustekveikja Energi and NorgesEnergi care about what Hafslund Strøm does for price decreases. Lærdal Energi, Gudbrandsdal Energi, and NorgesEnergi care about negative price adjustments made by Fitjar Kraftlag. Whereas a few retailers appear to be sometimes a price leader other times a price follower. In addition, results show that Hafslund Strøm seems to infer what Ustekveikja Energi and NorgesEnergi do for negative price adjustments.

For positive price adjustments, 5 out of 14 significant APEs suggest retailers immediately follow a price adjustment performed by Hafslund Strøm. Whereas Fortum Markets, Lyse, Telinet Energi, Total Energi, and Haugaland Energi appear to be sometimes a price leader other times price follower candidates. Fitjar Kraftlag, Luster Energiverk, and Lærdal Energi all seem to hold price leader positions to some extend. Furthermore, results indicate that Ustekveikja Energi, Gudbrandsdal Energi, and Norges Energi are price follower candidates for positive price adjustments.

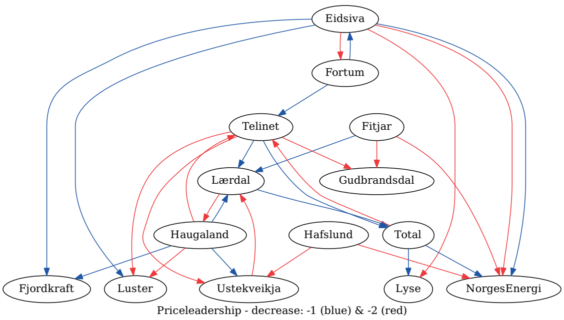


Figure 3: Pricing dynamics down comprising pricing states -1 (blue) and -2 (red)

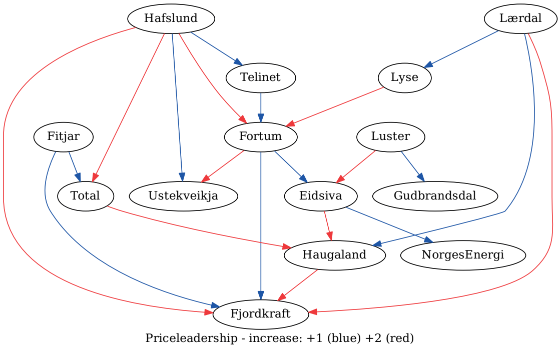


Figure 4: Pricing dynamics up comprising pricing states +1 (blue) and +2 (red)

Once it is determined that there are distinct pricing patterns and that specific retailers choose pricing strategies which resembles that of price leadership, we argue that the hypothesis of no mimicking of price adjustments made by others can be rejected. That said, as to further elaborate retailers into specific leadership types (barometric or strategic) a throughout assessment of estimation results in contribution with a qualitative evaluation of summary statistics (price rank, number and size of price adjustments) are of essential importance.

Numerous small price adjustment down and high APE-values for price margins on state probabilities in contribution with the apparent picture shown in Figure 3, add to the suspicion that Eidsiva Market holds a position which resembles that of a barometric price leader for price decreases. Whereas NorgesEnergi, Fjordkraft, Ustekveikja Energi, and Gudbrandsdal Energi seem to exhibit pricing strategies resembling that of barometric followers. Thus, they follow the barometric leader, margins seem to matter for pricing decisions, and they perform numerous small price adjustments. Furthermore, results show that Luster Energiverk and Lyse are more prone to be strategic price followers. Hence, they follow price leaders that perform relatively infrequent price adjustments and seem less concerned about margin size. In addition, we notice from our results that Haugaland Energi and Lærdal Energi seem to be sometimes a leader other times a follower. The same results can be observed for Eidsiva Market and Fortum Markets.

For positive price adjustments summary statistics and APE-values evaluated in contribution with the pricing dynamics in Figure 4 infer that Hafslund Strøm's pricing behavior is more likely to resemble that of a strategic leader than a barometric leader. Thus, Hafslund Strøm seems to increase prices without necessarily being squeezed on the margin and other retailers follow. Thus, Hafslund's pricing behavior seems to induce pricing decisions of other retailers to a large extent.

Estimation results for Fjordkraft show high APE-values indicating margin sensitivity and numerous small price adjustments. This coincides with that of a barometric price follower. Results for Fortum Markets and Total Energi show pricing patterns that bear resemblance to that of strategic price following; adjustments are fairly large and sparse in number. Furthermore, Gudbrandsdal Energi, and Eidsiva Marked are more likely to be barometric followers due to small and numerous adjustments for price increases and high APE-values of price margins on state transition probabilities.

Results from the IOHMM estimation given observed data of other retailers price adjustments add weight to the earlier suspicion that there are different price leadership types in this market, and that retailers differ in their pricing strategies. This impression is further strengthened when we evaluate results from the summary statistics in contribution with the IOHMM-estimation results comprising data on other retailers price adjustments. From an elaboration of the above, we argue that the hypothesis of no price leaders in this market can be rejected, and that there seem to be retailers that can be designated into roles as strategic and barometric price leaders. Thus, adding support to the suspicion that retailers employ available and timely information provided by the official price comparison site as to strategically set prices above the competitive level.

## 6 Conclusions

In this paper we examine retailers' pricing behavior as to gain new insight into if accurate and timely information accessible to retailers about the pricing behavior of other retailers facilitate price coordination. The issue of collusive behavior and the "dark side" of price transparency has not received much attention in the research literature on electricity retail markets.

The analysis in this paper is novel in two respects. First, we have a dataset with daily price data showing the precise pricing behavior of the retailers. Second, we use a hidden Markov model with time-varying transition probabilities to estimate and test the influence of own price margin and the pricing behavior of the other retailers on a retailer's price change decisions.

First, results show an asymmetry in retailers price adjustments. Thus, retailers are more prone to adjust prices up than down following an adjustment in margin size. Furthermore, results indicate that retailers differ in how prone they are to enter a different pricing state following an adjustment in margin size. Additionally, results suggest that some retailers are more prone to shift pricing strategy following an adjustment in margin size than others. In addition, the results from the input-output hidden Markov model estimation on price adjustments given data on other retailers price adjustments show that certain retailers seem to hold positions as leaders/followers, and that some exhibit pricing strategies that resemble that of barometric leaders/followers. Hence, the extensive evaluation of qualitative observations from summary statistics in contribution with estimation results show that accurate and timely information accessible from the official price comparison site has affected retailers pricing behavior. Thus, we reject the hypothesis of no mimicking of prices and no price leadership in this market.

From an overarching perspective, findings contribute to new insights about the performance of one of the first fully transparent electricity retail markets. More specifically, findings contribute to new insight about retailers' pricing behavior and the "dark side" of price transparency. Although we cannot conclude from our results that strategic collusion takes place in this market, we have shown that timely and accurate information has led to quicker adjustments for price increases. Thus, this represents a significant increase in costs to an average Norwegian households with a variable price contract.

With this new insight in place, we argue that it might be timely to ask and evaluate if information has become too transparent in electricity retail markets. In addition, our results emphasize the importance of looking beyond a seemingly successful market structure to detect sources of inefficiency, and target these sources as to facilitate an efficient expansion of electricity retail markets in the long run. Although results bring evidence that there seem to be both strategic and barometric price leadership, we have not identified whether these pricing regimes take place simultaneously or in different periods. This question is left for further research.

From a theoretical perspective, an efficient approach to deal with asymmetric pricing and pricing strategies that enable prices to persist above the competitive equilibrium is that consumers punish retailers by choosing the best deal. This will reduce asymmetry costs and make retailers set competitive prices. However, as documented by Fange (2021c), one needs to be aware of obstacles such as consumer inertia and other factors that hold back mobility of consumers in electricity retail markets.

# A Tables

## A.1 Summary stats

Table 3 comprises the summary statistics of mean price margins in percent for retailers in the sample.

Table 3: Summary statistics of price margins (percent). $N = 1817$.

| Retailer | Mean | StdDev | Min | Max |
|---|---|---|---|---|
| Eidsiva Marked | 43.4 | 22.1 | -25.0 | 172.0 |
| Fitjar Kraftlag | 37.5 | 24.0 | -21.0 | 149.0 |
| Fjordkraft | 39.9 | 22.9 | -28.0 | 153.0 |
| Fortum Markets | 50.6 | 27.7 | -20.0 | 218.0 |
| Gudbrandsdal Energi | 36.2 | 23.4 | -26.0 | 151.0 |
| Hafslund Strøm | 38.3 | 23.8 | -23.0 | 149.0 |
| Haugaland Energi | 31.8 | 28.1 | -37.0 | 155.0 |
| Luster Energiverk | 37.2 | 23.7 | -20.0 | 154.0 |
| Lyse | 37.5 | 23.2 | -30.0 | 146.0 |
| Lærdal Energi | 31.8 | 24.3 | -29.0 | 140.0 |
| NorgesEnergi | 32.5 | 23.6 | -35.0 | 139.0 |
| Telinet Energi | 35.5 | 25.2 | -37.0 | 145.0 |
| Total Energi | 33.6 | 24.7 | -40.0 | 141.0 |
| Ustekveikja Energi | 36.4 | 23.4 | -25.0 | 143.0 |

## A.2 Tobit models for price changes

Table 4 comprises the estimation results from the Censored (tobit) regression and should be interpreted as follows: the $\alpha$ represents the parameter estimate for the constant term and $\beta$ represents the parameter estimate for the margin. To evaluate the significance of margin size on price adjustments (for specific states) $\beta$-values for the parameter estimates are evaluated.

Table 4: Estimated parameters for the Tobit models.

| | State: -2 | | | State: -1 | | | State: 1 | | | State: 2 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Seller | $\alpha$ | $\beta$ | $\sigma$ | $\alpha$ | $\beta$ | $\sigma$ | $\alpha$ | $\beta$ | $\sigma$ | $\alpha$ | $\beta$ | s |
| Eidsiva Marked | 1.27 | 0.89 | 1.02 | -10.03 | 20.40 | 2.25 | 7.47 | -8.64 | 2.71 | 3.07 | -2.78 | 1.11 |
| | (0.38) | (0.63) | (0.09) | (3.14) | (3.72) | (0.73) | (1.48) | (7.35) | (0.67) | (0.28) | (0.89) | (0.11) |
| Fitjar Kraftlag | 1.93 | 0.81 | 1.10 | -5.99 | 19.30 | 1.43 | 3.90 | -0.29 | 1.83 | 7.08 | -14.86 | 3.08 |
| | (0.52) | (0.83) | (0.13) | (1.34) | (1.97) | (0.36) | (1.03) | (6.15) | (0.58) | (0.82) | (4.09) | (0.43) |
| Fjordkraft | 1.07 | 0.87 | 0.80 | -4.57 | 13.27 | 2.77 | 10.42 | -29.22 | 4.92 | 3.35 | -4.50 | 1.09 |
| | (0.33) | (0.55) | (0.07) | (3.67) | (4.61) | (0.71) | (2.01) | (11.04) | (1.15) | (0.28) | (1.12) | (0.12) |
| Fortum Markets | 0.64 | 3.14 | 1.14 | -2.65 | 14.91 | 0.74 | 20.19 | -45.64 | 3.13 | 6.57 | -9.05 | 1.32 |
| | (0.65) | (0.84) | (0.14) | (0.88) | (1.05) | (0.23) | (3.05) | (9.49) | (0.99) | (0.41) | (1.54) | (0.18) |
| Gudbrandsdal Energi | 1.16 | 0.10 | 0.90 | -12.14 | 24.33 | 3.56 | 12.46 | -34.22 | 4.52 | 3.30 | -6.82 | 1.35 |
| | (0.30) | (0.51) | (0.08) | (5.70) | (7.52) | (0.82) | (2.18) | (9.73) | (1.08) | (0.31) | (1.59) | (0.17) |
| Hafslund Strøm | 1.23 | 0.95 | 0.99 | 2.40 | 5.69 | 1.89 | 9.56 | 12.18 | 2.93 | 3.11 | -3.28 | 1.13 |
| | (0.40) | (0.64) | (0.10) | (2.67) | (3.33) | (0.48) | (1.08) | (10.74) | (0.73) | (0.33) | (1.54) | (0.14) |
| Haugaland Energi | 2.33 | -0.70 | 1.00 | -0.08 | 6.11 | 1.52 | 7.20 | -20.24 | 2.83 | 4.44 | -5.41 | 2.77 |
| | (0.53) | (0.93) | (0.12) | (0.85) | (1.33) | (0.25) | (1.26) | (6.14) | (0.82) | (0.56) | (2.82) | (0.39) |
| Luster Energiverk | 2.03 | -0.00 | 0.74 | -1.94 | 10.57 | 2.52 | 2.59 | 11.16 | 0.70 | 5.67 | -11.14 | 1.92 |
| | (0.43) | (0.64) | (0.10) | (2.54) | (3.72) | (0.50) | (0.67) | (3.04) | (0.29) | (0.46) | (2.45) | (0.26) |
| Lyse | 2.08 | -0.14 | 1.04 | -5.65 | 16.21 | 1.92 | 9.57 | -23.01 | 2.61 | 3.94 | -5.17 | 1.07 |
| | (0.44) | (0.74) | (0.11) | (1.90) | (2.59) | (0.45) | (1.23) | (7.42) | (0.60) | (0.28) | (1.35) | (0.15) |
| Lærdal Energi | 0.04 | 3.11 | 0.99 | -4.18 | 16.40 | 1.38 | 5.81 | -6.36 | 1.94 | 2.22 | -0.07 | 0.52 |
| | (0.41) | (0.77) | (0.10) | (1.30) | (1.98) | (0.37) | (0.53) | (2.56) | (0.35) | (0.11) | (0.63) | (0.08) |
| NorgesEnergi | 1.03 | 0.84 | 1.03 | -6.29 | 16.99 | 2.07 | 7.94 | -32.93 | 4.91 | 4.23 | -8.22 | 1.02 |
| | (0.31) | (0.58) | (0.09) | (2.66) | (3.68) | (0.56) | (2.18) | (18.59) | (1.47) | (0.21) | (1.18) | (0.13) |
| Telinet Energi | 1.35 | 1.88 | 1.19 | -0.02 | 8.18 | 1.91 | 14.84 | -29.41 | 5.46 | 5.65 | -10.36 | 1.87 |
| | (0.55) | (0.88) | (0.14) | (2.21) | (2.95) | (0.46) | (2.69) | (11.05) | (1.90) | (0.51) | (2.86) | (0.30) |
| Total Energi | 2.67 | 0.02 | 2.31 | -3.95 | 11.42 | 2.02 | 10.37 | -18.16 | 5.53 | 5.26 | -14.78 | 1.46 |
| | (1.34) | (2.46) | (0.33) | (1.34) | (1.97) | (0.31) | (2.18) | (9.72) | (1.33) | (0.40) | (1.98) | (0.22) |
| Ustekveikja Energi | 0.95 | 0.27 | 0.72 | -5.32 | 14.47 | 2.09 | 2.50 | -1.34 | 0.53 | 5.64 | -11.18 | 2.16 |
| | (0.26) | (0.43) | (0.07) | (2.02) | (3.01) | (0.38) | (0.22) | (0.94) | (0.11) | (0.50) | (3.09) | (0.31) |

Standard errors in parenthesis.

## A.3 Estimated transition probabilities from state 0

Table 5 shows the obtained predicted values which assign the probability of a transition to a different pricing regime from a change in margin. Estimation results should be interpreted such that the estimated APE-values corresponds with an adjustment in margin size by 100 øre/kWh.

Table 5: Estimated average partial effects (APEs) of price margins on state transition probabilities.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 8.987 | 1.252 | -2.001 | -9.920 | 63.59 | 0.000 |
| | ( 1.828) | ( 0.643) | ( 0.971) | ( 2.062) | | |
| Fitjar Kraftlag | 6.114 | 1.600 | -1.123 | -6.846 | 59.62 | 0.000 |
| | ( 1.347) | ( 0.729) | ( 0.675) | ( 1.857) | | |
| Fjordkraft | 9.344 | 2.222 | -1.959 | -8.094 | 68.28 | 0.000 |
| | ( 1.789) | ( 0.918) | ( 0.811) | ( 1.874) | | |
| Fortum Markets | 3.871 | 0.288 | -0.832 | -6.779 | 52.45 | 0.000 |
| | ( 0.967) | ( 0.324) | ( 0.728) | ( 1.557) | | |
| Gudbrandsdal Energi | 10.281 | 3.008 | -1.733 | -6.964 | 75.67 | 0.000 |
| | ( 1.787) | ( 0.976) | ( 0.941) | ( 1.809) | | |
| Hafslund Strøm | 9.312 | 2.455 | -2.313 | -7.742 | 80.26 | 0.000 |
| | ( 1.693) | ( 0.896) | ( 1.087) | ( 2.036) | | |
| Haugaland Energi | 5.963 | 2.985 | -0.605 | -5.639 | 67.56 | 0.000 |
| | ( 1.304) | ( 0.946) | ( 0.516) | ( 1.421) | | |
| Luster Energiverk | 5.769 | 2.373 | -0.297 | -7.053 | 64.48 | 0.000 |
| | ( 1.266) | ( 0.843) | ( 0.453) | ( 1.782) | | |
| Lyse | 4.618 | 2.747 | -1.982 | -6.464 | 57.28 | 0.000 |
| | ( 1.366) | ( 0.812) | ( 0.903) | ( 1.648) | | |
| Lærdal Energi | 5.911 | 1.105 | -3.096 | -7.179 | 58.03 | 0.000 |
| | ( 1.522) | ( 0.633) | ( 1.081) | ( 1.800) | | |
| NorgesEnergi | 9.189 | 2.257 | -2.029 | -6.291 | 61.99 | 0.000 |
| | ( 1.899) | ( 0.862) | ( 0.929) | ( 1.603) | | |
| Telinet Energi | 6.313 | 2.181 | -0.742 | -4.438 | 54.75 | 0.000 |
| | ( 1.383) | ( 0.819) | ( 0.566) | ( 1.419) | | |
| Total Energi | 3.908 | 4.387 | -1.429 | -4.244 | 57.17 | 0.000 |
| | ( 1.193) | ( 1.134) | ( 0.777) | ( 1.286) | | |
| Ustekveikja Energi | 10.046 | 4.188 | -1.614 | -6.028 | 77.95 | 0.000 |
| | ( 1.809) | ( 1.225) | ( 0.949) | ( 1.593) | | |

Bootstrap errors in parenthesis.

# B Estimated APE-values from the IOHMM given price adjustments initialized by other retailers price adjustments

Tables 6 - 19 comprise the estimation results from the IOHMM on price adjustments given data of other retailers price adjustments.

Table 6: Eidsiva Marked: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Fitjar Kraftlag | -0.0179 | 0.0022 | 0.0046 | -0.0285 | 7.75 | 0.000 |
| | (0.0110) | (0.0023) | (0.0041) | (0.0063) | | |
| Fjordkraft | -0.0040 | 0.0010 | -0.0017 | 0.0062 | 0.66 | 0.979 |
| | (0.0123) | (0.0014) | (0.0025) | (0.0122) | | |
| Fortum Markets | -0.0330 | 0.0080 | 0.0128 | -0.0115 | 13.56 | 0.000 |
| | (0.0079) | (0.0036) | (0.0058) | (0.0104) | | |
| Gudbrandsdal Energi | -0.0017 | -0.0028 | -0.0012 | -0.0059 | 1.08 | 0.882 |
| | (0.0104) | (0.0024) | (0.0031) | (0.0108) | | |
| Hafslund Strøm | -0.0265 | -0.0041 | 0.0080 | -0.0201 | 11.63 | 0.000 |
| | (0.0082) | (0.0024) | (0.0042) | (0.0086) | | |
| Haugaland Energi | -0.0158 | 0.0034 | 0.0070 | -0.0092 | 4.51 | 0.000 |
| | (0.0104) | (0.0020) | (0.0044) | (0.0108) | | |
| Luster Energiverk | -0.0021 | 0.0011 | 0.0103 | -0.0030 | 3.53 | 0.014 |
| | (0.0142) | (0.0049) | (0.0051) | (0.0142) | | |
| Lyse | -0.0089 | -0.0027 | -0.0031 | -0.0142 | 3.06 | 0.053 |
| | (0.0135) | (0.0021) | (0.0030) | (0.0108) | | |
| Lærdal Energi | 0.0325 | -0.0007 | 0.0019 | 0.0169 | 8.79 | 0.000 |
| | (0.0169) | (0.0019) | (0.0035) | (0.0140) | | |
| NorgesEnergi | 0.0157 | -0.0046 | 0.0029 | -0.0323 | 11.02 | 0.000 |
| | (0.0123) | (0.0028) | (0.0031) | (0.0055) | | |
| Telinet Energi | -0.0058 | 0.0036 | -0.0047 | 0.0132 | 2.81 | 0.095 |
| | (0.0142) | (0.0024) | (0.0029) | (0.0158) | | |
| Total Energi | -0.0079 | 0.0012 | -0.0006 | -0.0045 | 0.58 | 0.987 |
| | (0.0121) | (0.0029) | (0.0039) | (0.0116) | | |
| Ustekveikja Energi | 0.0038 | 0.0092 | 0.0016 | -0.0207 | 6.15 | 0.000 |
| | (0.0124) | (0.0051) | (0.0035) | (0.0071) | | |

Bootstrap standard errors in parenthesis.

Table 7: Fitjar Kraftlag: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0134 | -0.0006 | -0.0016 | -0.0015 | 3.28 | 0.030 |
| | (0.0076) | (0.0031) | (0.0031) | (0.0061) | | |
| Fjordkraft | 0.0095 | -0.0067 | 0.0005 | -0.0066 | 4.71 | 0.000 |
| | (0.0095) | (0.0023) | (0.0028) | (0.0061) | | |
| Fortum Markets | 0.0077 | -0.0036 | 0.0118 | -0.0106 | 9.09 | 0.000 |
| | (0.0092) | (0.0021) | (0.0063) | (0.0054) | | |
| Gudbrandsdal Energi | 0.0020 | -0.0060 | -0.0046 | -0.0081 | 4.30 | 0.001 |
| | (0.0086) | (0.0020) | (0.0020) | (0.0045) | | |
| Hafslund Strøm | -0.0058 | 0.0046 | 0.0125 | -0.0018 | 8.62 | 0.000 |
| | (0.0070) | (0.0065) | (0.0075) | (0.0070) | | |
| Haugaland Energi | 0.0189 | 0.0073 | 0.0128 | -0.0150 | 13.38 | 0.000 |
| | (0.0111) | (0.0063) | (0.0086) | (0.0036) | | |
| Luster Energiverk | -0.0053 | -0.0043 | -0.0027 | 0.0117 | 3.28 | 0.029 |
| | (0.0078) | (0.0028) | (0.0023) | (0.0133) | | |
| Lyse | 0.0056 | -0.0057 | 0.0025 | 0.0153 | 4.80 | 0.000 |
| | (0.0104) | (0.0021) | (0.0046) | (0.0117) | | |
| Lærdal Energi | 0.0046 | -0.0058 | -0.0055 | -0.0049 | 2.35 | 0.239 |
| | (0.0091) | (0.0018) | (0.0024) | (0.0080) | | |
| NorgesEnergi | -0.0162 | 0.0128 | -0.0041 | -0.0040 | 11.90 | 0.000 |
| | (0.0063) | (0.0085) | (0.0021) | (0.0068) | | |
| Telinet Energi | 0.0068 | -0.0001 | -0.0018 | 0.0096 | 1.73 | 0.560 |
| | (0.0088) | (0.0033) | (0.0030) | (0.0092) | | |
| Total Energi | 0.0081 | 0.0142 | 0.0060 | 0.0028 | 8.31 | 0.000 |
| | (0.0093) | (0.0075) | (0.0046) | (0.0078) | | |
| Ustekveikja Energi | -0.0085 | -0.0008 | -0.0025 | 0.0069 | 2.55 | 0.165 |
| | (0.0070) | (0.0030) | (0.0025) | (0.0093) | | |

Bootstrap standard errors in parenthesis.

Table 8: Fjordkraft: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0278 | -0.0020 | 0.0046 | 0.0090 | 10.16 | 0.000 |
| | (0.0115) | (0.0035) | (0.0025) | (0.0077) | | |
| Fitjar Kraftlag | -0.0091 | 0.0036 | 0.0114 | 0.0254 | 11.87 | 0.000 |
| | (0.0111) | (0.0037) | (0.0051) | (0.0130) | | |
| Fortum Markets | -0.0113 | 0.0083 | 0.0172 | -0.0059 | 12.43 | 0.000 |
| | (0.0104) | (0.0054) | (0.0057) | (0.0086) | | |
| Gudbrandsdal Energi | -0.0056 | -0.0030 | -0.0028 | 0.0122 | 2.71 | 0.119 |
| | (0.0102) | (0.0028) | (0.0034) | (0.0106) | | |
| Hafslund Strøm | 0.0028 | 0.0048 | 0.0085 | 0.0116 | 6.63 | 0.000 |
| | (0.0110) | (0.0028) | (0.0034) | (0.0116) | | |
| Haugaland Energi | 0.0272 | 0.0116 | 0.0113 | 0.0152 | 19.38 | 0.000 |
| | (0.0144) | (0.0045) | (0.0042) | (0.0117) | | |
| Luster Energiverk | 0.0162 | 0.0061 | 0.0014 | 0.0156 | 5.63 | 0.000 |
| | (0.0145) | (0.0034) | (0.0032) | (0.0138) | | |
| Lyse | -0.0068 | -0.0020 | -0.0006 | 0.0099 | 1.50 | 0.691 |
| | (0.0112) | (0.0022) | (0.0029) | (0.0117) | | |
| Lærdal Energi | 0.0105 | 0.0017 | 0.0120 | -0.0067 | 7.84 | 0.000 |
| | (0.0121) | (0.0027) | (0.0051) | (0.0073) | | |
| NorgesEnergi | 0.0038 | -0.0006 | 0.0005 | -0.0194 | 5.36 | 0.000 |
| | (0.0108) | (0.0020) | (0.0033) | (0.0059) | | |
| Telinet Energi | 0.0151 | 0.0036 | 0.0060 | 0.0116 | 4.63 | 0.000 |
| | (0.0153) | (0.0030) | (0.0048) | (0.0144) | | |
| Total Energi | 0.0003 | 0.0034 | -0.0047 | -0.0017 | 1.74 | 0.554 |
| | (0.0131) | (0.0036) | (0.0027) | (0.0090) | | |
| Ustekveikja Energi | -0.0014 | -0.0043 | -0.0019 | -0.0139 | 4.12 | 0.002 |
| | (0.0109) | (0.0027) | (0.0030) | (0.0073) | | |

Bootstrap standard errors in parenthesis.

Table 9: Fortum Markets: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0218 | 0.0007 | 0.0045 | -0.0052 | 10.40 | 0.000 |
| | (0.0085) | (0.0025) | (0.0024) | (0.0054) | | |
| Fitjar Kraftlag | 0.0070 | 0.0006 | 0.0005 | -0.0003 | 0.67 | 0.979 |
| | (0.0083) | (0.0033) | (0.0021) | (0.0073) | | |
| Fjordkraft | 0.0031 | -0.0047 | -0.0069 | 0.0082 | 6.54 | 0.000 |
| | (0.0077) | (0.0024) | (0.0033) | (0.0077) | | |
| Gudbrandsdal Energi | -0.0176 | -0.0001 | 0.0037 | 0.0006 | 7.19 | 0.000 |
| | (0.0058) | (0.0021) | (0.0031) | (0.0072) | | |
| Hafslund Strøm | -0.0115 | 0.0078 | 0.0081 | -0.0052 | 11.02 | 0.000 |
| | (0.0062) | (0.0039) | (0.0038) | (0.0057) | | |
| Haugaland Energi | 0.0124 | 0.0026 | 0.0004 | 0.0092 | 3.65 | 0.010 |
| | (0.0100) | (0.0035) | (0.0027) | (0.0095) | | |
| Luster Energiverk | 0.0069 | 0.0013 | 0.0076 | -0.0064 | 3.82 | 0.006 |
| | (0.0108) | (0.0037) | (0.0044) | (0.0072) | | |
| Lyse | 0.0001 | 0.0029 | 0.0104 | -0.0161 | 10.71 | 0.000 |
| | (0.0092) | (0.0041) | (0.0045) | (0.0046) | | |
| Lærdal Energi | 0.0204 | -0.0010 | -0.0037 | 0.0007 | 6.73 | 0.000 |
| | (0.0106) | (0.0033) | (0.0017) | (0.0079) | | |
| NorgesEnergi | 0.0148 | -0.0001 | -0.0043 | -0.0050 | 5.79 | 0.000 |
| | (0.0085) | (0.0031) | (0.0022) | (0.0056) | | |
| Telinet Energi | -0.0046 | 0.0005 | 0.0013 | 0.0277 | 8.08 | 0.000 |
| | (0.0075) | (0.0031) | (0.0027) | (0.0134) | | |
| Total Energi | 0.0149 | 0.0001 | 0.0041 | 0.0027 | 4.15 | 0.002 |
| | (0.0114) | (0.0029) | (0.0035) | (0.0090) | | |
| Ustekveikja Energi | 0.0012 | 0.0023 | -0.0028 | 0.0094 | 2.48 | 0.189 |
| | (0.0084) | (0.0030) | (0.0023) | (0.0098) | | |

Bootstrap standard errors in parenthesis.

Table 10: Gudbrandsdal Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0205 | -0.0007 | -0.0069 | 0.0035 | 7.09 | 0.000 |
| | (0.0103) | (0.0032) | (0.0039) | (0.0068) | | |
| Fitjar Kraftlag | -0.0093 | 0.0097 | 0.0008 | -0.0018 | 4.47 | 0.001 |
| | (0.0109) | (0.0045) | (0.0037) | (0.0079) | | |
| Fjordkraft | 0.0139 | 0.0018 | 0.0052 | -0.0040 | 3.71 | 0.008 |
| | (0.0102) | (0.0026) | (0.0032) | (0.0066) | | |
| Fortum Markets | -0.0057 | 0.0021 | 0.0009 | 0.0116 | 1.98 | 0.414 |
| | (0.0104) | (0.0032) | (0.0038) | (0.0117) | | |
| Hafslund Strøm | 0.0249 | -0.0023 | 0.0080 | 0.0030 | 8.29 | 0.000 |
| | (0.0128) | (0.0031) | (0.0053) | (0.0079) | | |
| Haugaland Energi | -0.0019 | 0.0068 | 0.0032 | -0.0138 | 5.14 | 0.000 |
| | (0.0110) | (0.0042) | (0.0050) | (0.0052) | | |
| Luster Energiverk | 0.0164 | -0.0022 | 0.0166 | -0.0037 | 9.41 | 0.000 |
| | (0.0142) | (0.0031) | (0.0078) | (0.0077) | | |
| Lyse | -0.0053 | 0.0034 | -0.0052 | 0.0205 | 6.47 | 0.000 |
| | (0.0107) | (0.0039) | (0.0035) | (0.0114) | | |
| Lærdal Energi | 0.0123 | -0.0058 | 0.0055 | -0.0022 | 4.14 | 0.002 |
| | (0.0116) | (0.0022) | (0.0044) | (0.0086) | | |
| NorgesEnergi | -0.0074 | 0.0004 | -0.0018 | -0.0048 | 1.07 | 0.887 |
| | (0.0114) | (0.0025) | (0.0033) | (0.0076) | | |
| Telinet Energi | -0.0142 | 0.0119 | 0.0077 | 0.0009 | 9.00 | 0.000 |
| | (0.0105) | (0.0046) | (0.0060) | (0.0098) | | |
| Total Energi | 0.0122 | 0.0004 | -0.0004 | 0.0207 | 5.34 | 0.000 |
| | (0.0128) | (0.0035) | (0.0033) | (0.0117) | | |
| Ustekveikja Energi | -0.0040 | 0.0006 | -0.0017 | 0.0033 | 0.41 | 0.997 |
| | (0.0112) | (0.0031) | (0.0035) | (0.0097) | | |

Bootstrap standard errors in parenthesis.

Table 11: Hafslund Strøm: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | -0.0186 | 0.0005 | 0.0037 | -0.0093 | 6.33 | 0.000 |
| | (0.0072) | (0.0035) | (0.0024) | (0.0068) | | |
| Fitjar Kraftlag | 0.0020 | 0.0002 | -0.0002 | -0.0101 | 1.17 | 0.849 |
| | (0.0108) | (0.0035) | (0.0036) | (0.0072) | | |
| Fjordkraft | -0.0087 | 0.0033 | 0.0079 | -0.0068 | 5.92 | 0.000 |
| | (0.0085) | (0.0045) | (0.0041) | (0.0070) | | |
| Fortum Markets | -0.0086 | -0.0011 | -0.0014 | -0.0054 | 0.94 | 0.926 |
| | (0.0107) | (0.0035) | (0.0037) | (0.0093) | | |
| Gudbrandsdal Energi | -0.0097 | 0.0041 | 0.0029 | -0.0082 | 3.63 | 0.010 |
| | (0.0103) | (0.0033) | (0.0037) | (0.0064) | | |
| Haugaland Energi | -0.0007 | -0.0038 | -0.0048 | -0.0132 | 3.39 | 0.022 |
| | (0.0108) | (0.0029) | (0.0023) | (0.0058) | | |
| Luster Energiverk | -0.0153 | 0.0028 | -0.0054 | -0.0097 | 4.04 | 0.003 |
| | (0.0098) | (0.0040) | (0.0021) | (0.0068) | | |
| Lyse | 0.0088 | 0.0081 | 0.0010 | 0.0075 | 3.45 | 0.018 |
| | (0.0158) | (0.0050) | (0.0034) | (0.0113) | | |
| Lærdal Energi | 0.0114 | 0.0062 | 0.0030 | -0.0035 | 4.14 | 0.002 |
| | (0.0122) | (0.0037) | (0.0039) | (0.0087) | | |
| NorgesEnergi | 0.0155 | -0.0059 | -0.0062 | -0.0189 | 11.13 | 0.000 |
| | (0.0114) | (0.0029) | (0.0023) | (0.0055) | | |
| Telinet Energi | 0.0016 | 0.0044 | 0.0026 | 0.0230 | 5.45 | 0.000 |
| | (0.0129) | (0.0037) | (0.0048) | (0.0150) | | |
| Total Energi | 0.0124 | 0.0054 | 0.0089 | 0.0050 | 7.08 | 0.000 |
| | (0.0127) | (0.0049) | (0.0047) | (0.0106) | | |
| Ustekveikja Energi | -0.0162 | -0.0071 | -0.0005 | 0.0079 | 6.30 | 0.000 |
| | (0.0099) | (0.0032) | (0.0041) | (0.0108) | | |

Bootstrap standard errors in parenthesis.

Table 12: Haugaland Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | -0.0120 | 0.0090 | 0.0114 | -0.0145 | 16.36 | 0.000 |
| | (0.0051) | (0.0062) | (0.0053) | (0.0049) | | |
| Fitjar Kraftlag | -0.0210 | 0.0115 | -0.0050 | -0.0060 | 8.53 | 0.000 |
| | (0.0044) | (0.0086) | (0.0023) | (0.0063) | | |
| Fjordkraft | -0.0159 | 0.0060 | 0.0110 | -0.0140 | 13.41 | 0.000 |
| | (0.0055) | (0.0067) | (0.0067) | (0.0044) | | |
| Fortum Markets | 0.0016 | -0.0112 | 0.0058 | 0.0048 | 5.17 | 0.000 |
| | (0.0110) | (0.0037) | (0.0066) | (0.0097) | | |
| Gudbrandsdal Energi | -0.0093 | 0.0010 | 0.0116 | -0.0029 | 5.86 | 0.000 |
| | (0.0065) | (0.0053) | (0.0075) | (0.0058) | | |
| Hafslund Strøm | 0.0034 | -0.0017 | -0.0014 | 0.0170 | 4.32 | 0.001 |
| | (0.0096) | (0.0053) | (0.0036) | (0.0117) | | |
| Luster Energiverk | 0.0203 | 0.0025 | -0.0071 | 0.0192 | 9.63 | 0.000 |
| | (0.0136) | (0.0076) | (0.0030) | (0.0171) | | |
| Lyse | -0.0018 | -0.0060 | -0.0045 | 0.0012 | 2.92 | 0.074 |
| | (0.0097) | (0.0053) | (0.0030) | (0.0074) | | |
| Lærdal Energi | -0.0046 | 0.0265 | 0.0192 | -0.0003 | 24.03 | 0.000 |
| | (0.0078) | (0.0096) | (0.0082) | (0.0078) | | |
| NorgesEnergi | 0.0213 | -0.0042 | -0.0007 | -0.0194 | 9.62 | 0.000 |
| | (0.0111) | (0.0052) | (0.0027) | (0.0039) | | |
| Telinet Energi | 0.0027 | -0.0012 | -0.0045 | 0.0107 | 2.28 | 0.269 |
| | (0.0106) | (0.0060) | (0.0024) | (0.0111) | | |
| Total Energi | 0.0074 | -0.0064 | -0.0038 | 0.0359 | 15.37 | 0.000 |
| | (0.0114) | (0.0041) | (0.0026) | (0.0157) | | |
| Ustekveikja Energi | -0.0284 | 0.0119 | -0.0025 | -0.0030 | 10.13 | 0.000 |
| | (0.0051) | (0.0071) | (0.0033) | (0.0066) | | |

Bootstrap standard errors in parenthesis.

Table 13: Luster Energiverk: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0147 | 0.0091 | -0.0017 | 0.0010 | 8.89 | 0.000 |
| | (0.0078) | (0.0040) | (0.0018) | (0.0062) | | |
| Fitjar Kraftlag | 0.0059 | -0.0045 | -0.0024 | -0.0002 | 1.71 | 0.568 |
| | (0.0093) | (0.0041) | (0.0014) | (0.0074) | | |
| Fjordkraft | -0.0040 | -0.0043 | -0.0007 | -0.0136 | 5.22 | 0.000 |
| | (0.0061) | (0.0030) | (0.0020) | (0.0061) | | |
| Fortum Markets | -0.0097 | 0.0092 | 0.0057 | 0.0196 | 10.69 | 0.000 |
| | (0.0050) | (0.0059) | (0.0045) | (0.0127) | | |
| Gudbrandsdal Energi | -0.0239 | 0.0076 | -0.0023 | 0.0117 | 15.77 | 0.000 |
| | (0.0054) | (0.0056) | (0.0011) | (0.0096) | | |
| Hafslund Strøm | 0.0028 | 0.0064 | 0.0010 | 0.0176 | 7.51 | 0.000 |
| | (0.0075) | (0.0043) | (0.0021) | (0.0092) | | |
| Haugaland Energi | -0.0019 | 0.0136 | 0.0092 | 0.0024 | 11.03 | 0.000 |
| | (0.0073) | (0.0066) | (0.0053) | (0.0076) | | |
| Lyse | 0.0045 | 0.0033 | -0.0019 | 0.0002 | 1.09 | 0.879 |
| | (0.0139) | (0.0050) | (0.0015) | (0.0083) | | |
| Lærdal Energi | 0.0028 | 0.0028 | 0.0056 | -0.0060 | 3.85 | 0.005 |
| | (0.0082) | (0.0050) | (0.0040) | (0.0060) | | |
| NorgesEnergi | -0.0091 | -0.0050 | -0.0027 | 0.0061 | 4.92 | 0.000 |
| | (0.0059) | (0.0037) | (0.0015) | (0.0079) | | |
| Telinet Energi | 0.0339 | 0.0038 | 0.0023 | 0.0141 | 15.30 | 0.000 |
| | (0.0125) | (0.0053) | (0.0028) | (0.0136) | | |
| Total Energi | 0.0021 | 0.0038 | -0.0013 | -0.0039 | 0.97 | 0.919 |
| | (0.0072) | (0.0066) | (0.0013) | (0.0075) | | |
| Ustekveikja Energi | 0.0159 | -0.0055 | 0.0047 | -0.0033 | 7.00 | 0.000 |
| | (0.0097) | (0.0044) | (0.0031) | (0.0066) | | |

Bootstrap standard errors in parenthesis.

Table 14: Lyse: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0014 | 0.0211 | -0.0007 | 0.0123 | 14.32 | 0.000 |
| | (0.0069) | (0.0062) | (0.0040) | (0.0068) | | |
| Fitjar Kraftlag | 0.0066 | -0.0032 | 0.0059 | 0.0027 | 2.57 | 0.158 |
| | (0.0101) | (0.0029) | (0.0057) | (0.0072) | | |
| Fjordkraft | 0.0024 | 0.0081 | 0.0023 | 0.0001 | 3.10 | 0.048 |
| | (0.0093) | (0.0051) | (0.0038) | (0.0068) | | |
| Fortum Markets | 0.0002 | -0.0052 | 0.0033 | 0.0071 | 3.06 | 0.053 |
| | (0.0090) | (0.0028) | (0.0044) | (0.0099) | | |
| Gudbrandsdal Energi | 0.0081 | 0.0010 | -0.0078 | -0.0019 | 3.62 | 0.011 |
| | (0.0088) | (0.0031) | (0.0029) | (0.0064) | | |
| Hafslund Strøm | 0.0152 | 0.0066 | 0.0057 | 0.0100 | 9.48 | 0.000 |
| | (0.0096) | (0.0035) | (0.0054) | (0.0084) | | |
| Haugaland Energi | 0.0209 | -0.0004 | 0.0011 | 0.0050 | 5.30 | 0.000 |
| | (0.0112) | (0.0028) | (0.0035) | (0.0080) | | |
| Luster Energiverk | -0.0112 | 0.0087 | 0.0014 | 0.0033 | 4.25 | 0.001 |
| | (0.0078) | (0.0061) | (0.0031) | (0.0081) | | |
| Lærdal Energi | 0.0177 | 0.0045 | 0.0218 | -0.0109 | 19.80 | 0.000 |
| | (0.0112) | (0.0049) | (0.0075) | (0.0044) | | |
| NorgesEnergi | 0.0046 | -0.0113 | -0.0015 | -0.0069 | 4.73 | 0.000 |
| | (0.0095) | (0.0035) | (0.0033) | (0.0047) | | |
| Telinet Energi | 0.0129 | -0.0007 | 0.0203 | 0.0046 | 11.06 | 0.000 |
| | (0.0105) | (0.0030) | (0.0105) | (0.0086) | | |
| Total Energi | -0.0095 | 0.0131 | -0.0036 | 0.0057 | 8.39 | 0.000 |
| | (0.0081) | (0.0063) | (0.0030) | (0.0083) | | |
| Ustekveikja Energi | 0.0047 | -0.0075 | 0.0005 | 0.0059 | 3.45 | 0.018 |
| | (0.0090) | (0.0030) | (0.0032) | (0.0079) | | |

Bootstrap standard errors in parenthesis.

Table 15: Lærdal Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0101 | 0.0037 | 0.0054 | 0.0000 | 3.74 | 0.007 |
| | (0.0080) | (0.0031) | (0.0055) | (0.0059) | | |
| Fitjar Kraftlag | -0.0088 | 0.0170 | 0.0045 | -0.0049 | 10.40 | 0.000 |
| | (0.0082) | (0.0063) | (0.0052) | (0.0061) | | |
| Fjordkraft | 0.0149 | -0.0057 | 0.0099 | -0.0088 | 9.71 | 0.000 |
| | (0.0097) | (0.0030) | (0.0055) | (0.0052) | | |
| Fortum Markets | -0.0129 | 0.0011 | 0.0038 | -0.0028 | 2.43 | 0.206 |
| | (0.0067) | (0.0029) | (0.0047) | (0.0086) | | |
| Gudbrandsdal Energi | 0.0005 | 0.0014 | -0.0059 | 0.0082 | 2.73 | 0.115 |
| | (0.0085) | (0.0022) | (0.0040) | (0.0077) | | |
| Hafslund Strøm | 0.0089 | -0.0002 | 0.0042 | 0.0157 | 5.32 | 0.000 |
| | (0.0090) | (0.0025) | (0.0043) | (0.0101) | | |
| Haugaland Energi | 0.0279 | -0.0013 | 0.0028 | 0.0102 | 8.87 | 0.000 |
| | (0.0122) | (0.0028) | (0.0051) | (0.0095) | | |
| Luster Energiverk | 0.0083 | -0.0014 | 0.0051 | 0.0185 | 5.00 | 0.000 |
| | (0.0106) | (0.0024) | (0.0069) | (0.0143) | | |
| Lyse | 0.0117 | 0.0084 | 0.0104 | -0.0136 | 12.44 | 0.000 |
| | (0.0107) | (0.0049) | (0.0068) | (0.0044) | | |
| NorgesEnergi | -0.0120 | -0.0004 | 0.0083 | -0.0063 | 5.04 | 0.000 |
| | (0.0086) | (0.0022) | (0.0064) | (0.0053) | | |
| Telinet Energi | 0.0046 | 0.0109 | -0.0076 | 0.0166 | 9.73 | 0.000 |
| | (0.0092) | (0.0048) | (0.0035) | (0.0132) | | |
| Total Energi | 0.0119 | -0.0053 | 0.0077 | 0.0008 | 5.08 | 0.000 |
| | (0.0103) | (0.0027) | (0.0078) | (0.0080) | | |
| Ustekveikja Energi | 0.0148 | 0.0061 | 0.0026 | -0.0029 | 5.46 | 0.000 |
| | (0.0093) | (0.0026) | (0.0061) | (0.0067) | | |

Bootstrap standard errors in parenthesis.

Table 16: NorgesEnergi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0324 | 0.0061 | 0.0016 | 0.0230 | 22.85 | 0.000 |
| | (0.0105) | (0.0021) | (0.0025) | (0.0088) | | |
| Fitjar Kraftlag | -0.0207 | 0.0079 | 0.0009 | 0.0001 | 5.53 | 0.000 |
| | (0.0103) | (0.0034) | (0.0025) | (0.0072) | | |
| Fjordkraft | -0.0067 | -0.0003 | -0.0049 | -0.0040 | 2.48 | 0.187 |
| | (0.0096) | (0.0017) | (0.0021) | (0.0074) | | |
| Fortum Markets | 0.0079 | 0.0011 | -0.0005 | -0.0016 | 0.54 | 0.990 |
| | (0.0121) | (0.0018) | (0.0024) | (0.0092) | | |
| Gudbrandsdal Energi | 0.0027 | 0.0031 | -0.0027 | 0.0058 | 1.90 | 0.463 |
| | (0.0112) | (0.0019) | (0.0019) | (0.0077) | | |
| Hafslund Strøm | 0.0062 | 0.0039 | 0.0061 | 0.0167 | 8.33 | 0.000 |
| | (0.0105) | (0.0016) | (0.0038) | (0.0090) | | |
| Haugaland Energi | 0.0082 | 0.0016 | 0.0037 | 0.0037 | 1.58 | 0.645 |
| | (0.0116) | (0.0024) | (0.0042) | (0.0093) | | |
| Luster Energiverk | 0.0088 | -0.0071 | -0.0033 | 0.0052 | 4.63 | 0.000 |
| | (0.0131) | (0.0024) | (0.0021) | (0.0112) | | |
| Lyse | 0.0202 | 0.0037 | 0.0041 | 0.0003 | 4.61 | 0.000 |
| | (0.0136) | (0.0022) | (0.0034) | (0.0078) | | |
| Lærdal Energi | 0.0104 | -0.0034 | 0.0022 | -0.0014 | 1.99 | 0.413 |
| | (0.0118) | (0.0022) | (0.0028) | (0.0074) | | |
| Telinet Energi | 0.0073 | 0.0013 | 0.0227 | -0.0112 | 11.27 | 0.000 |
| | (0.0127) | (0.0021) | (0.0114) | (0.0062) | | |
| Total Energi | 0.0124 | 0.0146 | 0.0118 | 0.0036 | 12.42 | 0.000 |
| | (0.0129) | (0.0047) | (0.0065) | (0.0083) | | |
| Ustekveikja Energi | 0.0067 | -0.0049 | -0.0008 | 0.0032 | 1.86 | 0.481 |
| | (0.0118) | (0.0029) | (0.0027) | (0.0076) | | |

Bootstrap standard errors in parenthesis.

Table 17: Telinet Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0013 | -0.0034 | 0.0010 | 0.0006 | 1.13 | 0.867 |
| | (0.0079) | (0.0027) | (0.0024) | (0.0052) | | |
| Fitjar Kraftlag | 0.0013 | 0.0007 | 0.0083 | -0.0052 | 3.34 | 0.025 |
| | (0.0089) | (0.0037) | (0.0044) | (0.0048) | | |
| Fjordkraft | 0.0204 | -0.0077 | 0.0010 | 0.0030 | 9.43 | 0.000 |
| | (0.0106) | (0.0026) | (0.0020) | (0.0065) | | |
| Fortum Markets | -0.0229 | 0.0119 | 0.0019 | -0.0106 | 13.44 | 0.000 |
| | (0.0050) | (0.0054) | (0.0027) | (0.0043) | | |
| Gudbrandsdal Energi | -0.0013 | -0.0050 | -0.0023 | -0.0008 | 2.36 | 0.235 |
| | (0.0075) | (0.0029) | (0.0018) | (0.0058) | | |
| Hafslund Strøm | 0.0086 | -0.0003 | 0.0093 | 0.0016 | 5.10 | 0.000 |
| | (0.0094) | (0.0026) | (0.0045) | (0.0060) | | |
| Haugaland Energi | 0.0055 | 0.0125 | 0.0013 | 0.0135 | 9.22 | 0.000 |
| | (0.0091) | (0.0056) | (0.0021) | (0.0106) | | |
| Luster Energiverk | 0.0094 | 0.0166 | 0.0137 | -0.0011 | 12.98 | 0.000 |
| | (0.0106) | (0.0087) | (0.0072) | (0.0084) | | |
| Lyse | -0.0006 | -0.0084 | -0.0032 | 0.0033 | 4.54 | 0.000 |
| | (0.0084) | (0.0028) | (0.0029) | (0.0078) | | |
| Lærdal Energi | 0.0182 | 0.0072 | 0.0049 | -0.0034 | 8.90 | 0.000 |
| | (0.0101) | (0.0057) | (0.0030) | (0.0060) | | |
| NorgesEnergi | -0.0053 | 0.0041 | 0.0018 | 0.0015 | 1.52 | 0.676 |
| | (0.0071) | (0.0032) | (0.0022) | (0.0064) | | |
| Total Energi | -0.0047 | 0.0121 | 0.0011 | 0.0048 | 7.16 | 0.000 |
| | (0.0079) | (0.0057) | (0.0020) | (0.0100) | | |
| Ustekveikja Energi | -0.0010 | -0.0066 | -0.0054 | 0.0134 | 7.66 | 0.000 |
| | (0.0084) | (0.0027) | (0.0033) | (0.0102) | | |

Bootstrap standard errors in parenthesis.

Table 18: Total Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0074 | -0.0026 | -0.0015 | -0.0039 | 2.15 | 0.328 |
| | (0.0056) | (0.0051) | (0.0032) | (0.0053) | | |
| Fitjar Kraftlag | 0.0039 | 0.0031 | -0.0047 | 0.0216 | 8.98 | 0.000 |
| | (0.0073) | (0.0068) | (0.0020) | (0.0107) | | |
| Fjordkraft | -0.0069 | 0.0062 | -0.0013 | -0.0021 | 2.44 | 0.203 |
| | (0.0056) | (0.0071) | (0.0049) | (0.0065) | | |
| Fortum Markets | -0.0046 | -0.0091 | -0.0000 | -0.0008 | 2.40 | 0.218 |
| | (0.0060) | (0.0053) | (0.0044) | (0.0070) | | |
| Gudbrandsdal Energi | -0.0209 | 0.0112 | -0.0006 | -0.0032 | 11.69 | 0.000 |
| | (0.0044) | (0.0063) | (0.0033) | (0.0061) | | |
| Hafslund Strøm | -0.0060 | 0.0107 | 0.0034 | 0.0269 | 14.76 | 0.000 |
| | (0.0059) | (0.0067) | (0.0038) | (0.0116) | | |
| Haugaland Energi | 0.0001 | -0.0018 | 0.0054 | 0.0016 | 1.16 | 0.852 |
| | (0.0073) | (0.0049) | (0.0054) | (0.0071) | | |
| Luster Energiverk | 0.0100 | -0.0050 | 0.0045 | -0.0068 | 3.80 | 0.006 |
| | (0.0105) | (0.0062) | (0.0090) | (0.0061) | | |
| Lyse | 0.0226 | -0.0160 | -0.0060 | -0.0038 | 8.89 | 0.000 |
| | (0.0131) | (0.0033) | (0.0021) | (0.0062) | | |
| Lærdal Energi | 0.0234 | -0.0078 | 0.0073 | -0.0079 | 14.90 | 0.000 |
| | (0.0100) | (0.0046) | (0.0066) | (0.0044) | | |
| NorgesEnergi | -0.0004 | -0.0042 | 0.0052 | -0.0048 | 2.74 | 0.113 |
| | (0.0063) | (0.0052) | (0.0037) | (0.0053) | | |
| Telinet Energi | 0.0406 | 0.0001 | 0.0144 | -0.0060 | 21.24 | 0.000 |
| | (0.0151) | (0.0063) | (0.0118) | (0.0059) | | |
| Ustekveikja Energi | -0.0049 | 0.0076 | -0.0021 | 0.0062 | 2.93 | 0.072 |
| | (0.0059) | (0.0064) | (0.0027) | (0.0071) | | |

Bootstrap standard errors in parenthesis.

Table 19: Ustekveikja Energi: Estimated average partial effects given observed data of other retailers price adjustments.

| | Price decrease states | | Price increase states | | Wald-test | |
|---|---|---|---|---|---|---|
| Retailer | -2 | -1 | 1 | 2 | $\chi^2$ | $p$-value |
| Eidsiva Marked | 0.0012 | 0.0039 | 0.0022 | -0.0006 | 0.91 | 0.935 |
| | (0.0086) | (0.0044) | (0.0033) | (0.0061) | | |
| Fitjar Kraftlag | 0.0086 | -0.0105 | -0.0070 | 0.0031 | 5.81 | 0.000 |
| | (0.0134) | (0.0047) | (0.0023) | (0.0072) | | |
| Fjordkraft | -0.0175 | -0.0093 | -0.0116 | 0.0045 | 11.50 | 0.000 |
| | (0.0087) | (0.0041) | (0.0030) | (0.0073) | | |
| Fortum Markets | -0.0055 | 0.0111 | 0.0216 | 0.0020 | 10.72 | 0.000 |
| | (0.0100) | (0.0072) | (0.0092) | (0.0072) | | |
| Gudbrandsdal Energi | -0.0010 | 0.0046 | 0.0042 | 0.0082 | 3.04 | 0.055 |
| | (0.0097) | (0.0052) | (0.0049) | (0.0069) | | |
| Hafslund Strøm | 0.0127 | 0.0112 | 0.0141 | 0.0122 | 15.12 | 0.000 |
| | (0.0112) | (0.0042) | (0.0067) | (0.0068) | | |
| Haugaland Energi | -0.0005 | 0.0239 | 0.0016 | 0.0005 | 12.54 | 0.000 |
| | (0.0108) | (0.0071) | (0.0041) | (0.0064) | | |
| Luster Energiverk | -0.0256 | 0.0062 | 0.0067 | 0.0049 | 6.24 | 0.000 |
| | (0.0080) | (0.0063) | (0.0109) | (0.0085) | | |
| Lyse | -0.0084 | -0.0020 | -0.0048 | 0.0141 | 4.69 | 0.000 |
| | (0.0108) | (0.0038) | (0.0030) | (0.0085) | | |
| Lærdal Energi | 0.0115 | 0.0027 | -0.0011 | 0.0002 | 1.42 | 0.730 |
| | (0.0118) | (0.0042) | (0.0036) | (0.0072) | | |
| NorgesEnergi | 0.0108 | -0.0110 | 0.0093 | -0.0094 | 9.56 | 0.000 |
| | (0.0107) | (0.0039) | (0.0065) | (0.0047) | | |
| Telinet Energi | 0.0126 | 0.0167 | 0.0078 | -0.0090 | 11.05 | 0.000 |
| | (0.0136) | (0.0081) | (0.0090) | (0.0053) | | |
| Total Energi | 0.0083 | 0.0060 | -0.0023 | 0.0177 | 6.61 | 0.000 |
| | (0.0120) | (0.0061) | (0.0031) | (0.0090) | | |

Bootstrap standard errors in parenthesis.

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## Kari-Anne Fange

Kari-Anne Fange was born March 1, 1980 in Halden, Norway. She holds a Master's degree and a Bachelor's degree in Economics and Resource Management from NMBU (2006; 2004). In addition, Fange has studied law and physical geography at the University of Oslo.

The thesis comprises an introduction chapter and four independent papers. In general, the thesis explores efficiency outcomes following the Norwegian electricity market reform introduced in the early 1990s. More specifically, the thesis analyzes efficiency outcomes resulting from the incentive regulation of electricity network companies, the inherent nature of household consumers and their attitudes to market participation, electricity price development. In addition, the thesis analyzes if accurate and timely information about electricity prices can serve as a facilitating tool for price coordination among retailers.

The first paper gives an overview of the benchmarking models used in Norwegian incentive regulation from 1997- to 2011. The paper discusses specific issues relating to development of the DEA models, including choice of scale assumptions and input and output variables, and examines how the results from the benchmarking models are used.

The second paper explores households' decision to switch electricity retailer, using a theoretical framework that embraces both economic and psychological influences. Results show that both issues related to market design and psychological factors seem important in inducing households' switch choices.

The third paper studies price dispersion in electricity contracts from the perspective that prices for homogeneous goods should converge according to the "law of one price". By a cointegrated VAR-framework the study finds that both switch activity and number of firms offering a specific contract are significantly reflected in price dispersion.

The final paper explores market behavior among nationwide electricity retailers. More specifically, the paper uses a Markov chain model of price changes to predict the probability that price adjustments made by electricity retailers stem from collusive behavior. Results suggest a pattern where certain retailers take on a price leader/follower position. Findings contribute to new insight about the "dark side" of price transparency in electricity retail markets.

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**ISSN: 1894-6402**
**ISBN: 978-82-575-1737-3**
**Thesis: 2021:66**

ISBN: 978-82-575-1737-3
ISSN: 1894-6402

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of Life Sciences

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